ESSAYS ON RESOURCE DEPENDENCE, INCOME AND LOCAL DEVELOPMENT OUTCOMES IN INDONESIA

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ABSTRACT

My thesis explores the effect of natural resource dependence on income and local development indicators at the district level in Indonesia. The thesis is comprised of five chapters, where the middle three chapters are the main empirical investigations.

Chapter One provides an introduction to the main questions of each chapter. Chapter Two starts the investigation of the resource curse in Indonesia by exploring the effect of resource dependence on district per capita income. Using annual fixed effects and first differenced regressions with and without newly constructed instruments, I find little evidence of a “resource curse”, but more a resource blessing.

Chapter Three questions why resource dependence is positively associated with per capita income in Indonesia. I test four potential causal mechanisms for this positive effect: spillovers to manufacturing, higher education provision, improvements in institutional quality, and investment in public capital. I first confirm a positive overall effect of resource dependence on real per capita Gross Regional Domestic Product. I then test the extent to which resource dependence positively affects manufacturing, education, district institutional quality, and public investment. I finally test the extent to which these factors in turn contribute to per capita income. I find that resource dependence aids income in part by raising measures of district institutional quality. Resource dependence also raises one measure of education, net high school enrolment rates, though I do not find that this in turn raises per capita income. Conversely, while higher capital spending by districts does raise income, I find no evidence that this share is affected by resource dependence. In auxiliary analysis, I find little support for the hypothesis that resource dependence benefits per capita income more (or only) for districts that begin with higher institutional quality.

Chapter Four finalises the investigation by testing the effect of resource dependence not only on income per capita but also on some other key development outcomes, namely the poverty rate, educational attainment (as opposed to enrolment) and life expectancy. In this chapter I also focus on the spatial spillover effects of neighbour district resource dependence on home district outcomes. The results again confirm my initial finding on per capita income, but with no significant effects found for poverty rates. In contrast, I find that home resource dependence is negatively associated with education attainment and with life expectancy measures, and that the effects of neighbour district resource dependence matters, sometimes in opposite ways to home district resource dependence.

Finally, Chapter Five summarises the empirical findings of the previous chapters.

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1 CHAPTER ONE

1.1 Introduction

Natural resources play an important role in the development of a country. While resource-poor nations entrench productivity by specializing in producing manufactured goods, resource-rich countries use their natural resources-based sectors to drive their economy. This reasoning strengthens our belief that natural resources lead to a positive effect on a country's economy, as most economists have postulated (Rostow, 1959; North, 1982; Barbier, 2005). It was quite surprising therefore when an initial empirical study by Sachs and Warner (1995) found contrary evidence that resource dependence reduces growth in per capita income, a finding which later became known as the resource curse phenomenon.

Subsequently, many such studies have used between-country data, and have provided relevant explanations of possible transmission channels that cause this negative relationship. Among them are crowding-out effects on the manufacturing sector, reducing human capital, weakening institutional quality, and worsening the quality of government spending. Yet the negative empirical findings regarding oil or mining, are not without critiques (van der Ploeg, 2011; Brunnschweiler, 2008), while several studies have also found mixed results (e.g. Brunnschweiler & Bulte, 2008; Ouoba, 2016). Even more striking, other recent studies conducted at the regional level generally contradict the curse effect of resources on income (e.g. Fleming, Measham, Paredes, 2015; Weber, 2014). Researchers who conduct these studies often stress the importance of within country analysis. Many of these studies provide better resource dependence measures, perform instrumental variable estimation, and use data at county level or local government level to minimise unobserved heterogeneity. More recent studies also control for the spatial effects of natural resources from neighbouring regions. This spatial analysis has appeared in the resource curse literature from 2015 onwards.

Indonesia on the other hand is a country rich in natural resources dominating resource output in the Southeast Asian region, and even Asia. However, a comprehensive study examining the effects of non-renewable natural resources on local per capita income in Indonesia is lacking. Moreover, studies exploring the effects of mining and oil, in particular, on broader development indicators sub-nationally such as poverty rates, education, and health are hard to find.

1.2 The Structure of the Thesis

The main aim of this thesis is to contribute empirically to the resource impact literature at the regional level. While a small number of studies have attempted to test resource effects at the county-level, these have concentrated on developed countries. My thesis examines the case of Indonesia in its post decentralisation era, but it may shed light on resource effects on other representative emerging countries, especially in Asia.

The thesis is comprised of three main chapters which are expected to satisfy the main objective of this research. CHAPTER TWO will first explain the natural resource curse hypothesis, providing a deep empirical review on the resource curse debate, including discussions regarding measurements of resource variables, possible endogeneity of resource dependence measures, and recent survey papers that emphasise the importance of within country analysis. By considering observations from 2005-2015 following the decentralisation era and using an instrumental variable strategy, the aim of this chapter is to provide empirical evidence of the impact of resource dependence measures on income in Indonesia.

CHAPTER THREE analyses the transmission channels through which resource dependence affects income at the district level. The specific transmission channels I will examine are crowding out or crowding in of non resource-based activity, education enrollment levels, institutional quality, and government spending/investment in capital.

Next, while my previous chapters focus on the association between resource dependence and per capita income, they say nothing about how resource dependence affects other measures of living standards or development. Thus, alternative outcome measures related to poverty, education and health will also be considered. In addition to considering the effects of resource dependence on alternative outcome measures, CHAPTER FOUR will also emphasise potential spatial spillover effects of resource dependence on adjoining districts. Controlling for spatial spillovers when estimating resource effects becomes more important as the unit of observation moves from nations (in between-country studies), to fine-grained districts. It may be that the estimated resource effects are heightened or diminished after spillover effects are controlled.

To conclude, CHAPTER FIVE summarizes this thesis by highlighting the core findings obtained in the main chapters.

2 CHAPTER TWO

An Investigation of the Resource Curse in Indonesia

2.1 Introduction

2.1.1 Background

In the 1960's, there was a strong belief that a country's natural resources determined the quality of its economic performance. A prominent proponent of this view was the development economist Walter Rostow, who argued that a country's natural resource endowment played a crucial role in its "take-off" process, or its period of transition from being a traditional society based on a primary sector to a more industrialized society with high consumption (Rostow, 1959).

Similarly, in the late 1980's, neo-classical economists such as Douglas North stressed the significance of natural resource stocks as a driving component of a society's long-term output (North, 1982).[1] North argued that, historically, natural resources played an essential role in the United States' transition to being a dominant economy by the early twentieth century. Natural resources have also been credited as the main factor behind the history of the great economic development of countries beyond the United States, such as Canada, Australia, and Finland, enabling them to outperform other countries' development in the world (Lederman and Maloney, 2008). Thus, until the late 1980's at least, natural resources were generally viewed by economists as an advantage that can sustain and promote economic growth without exception.

By the early 1990's, however, this positive view of the role of resources in development seemed to face an empirical challenge. Many nations with an abundance of natural resources, primarily located in Africa, the Middle East, and Latin America, have tended to have weak income levels and unstable growth rates and have obtained worse performance on broader development indicators when compared to resource-scarce countries elsewhere. Auty (1994) was the first to label this counter-intuitive result a "resource curse". This term can be defined as the negative impact of natural resource wealth on economic growth or economic

[1] North modelled the influence of natural resources using a society's aggregate production function $Y = F(N, T, R, P, H)$, where Y is output, N stands for the society's stock of knowledge, T denotes its technological stock, R is its endowment of natural resources, and P and H refer respectively to its stock of labour and human capital (See North (1982), pages 15-16).

performance.[2] In a more recent treatment, Humphreys, Sachs and Stiglitz (2007) emphasize the resource curse phenomenon using broader outcome measures than income or output, such as indicators of social development and good governance.

The first empirical paper to test Auty's "resource curse" was by Sachs and Warner (1995). Sachs and Warner conduct a large pooled cross-country study over twenty years (1970-1989) to test the relationship between what they called natural resource "abundance" and growth in income. They find an inverse association on average. Auty's proposed resource curse, and Sachs and Warner's confirmation of it, has sparked continuous attention from academics and practitioners. As of 2017, there have been hundreds of studies testing the relationship between natural resources and economic growth. These studies have been compiled and discussed in several surveys, which not only summarise some important findings in the previous empirical studies, but also criticize their methods and make suggestions for further analysis (Badeeb, Lean & Clark, 2017; Aragón, Chuhan-Pole and Land (2015); Cust and Poelhekke, 2015; Frankel, 2010; Papyrakis, 2016; van der Ploeg, 2011; van der Ploeg & Poelhekke, 2016).

Some studies have confirmed a negative and significant effect of natural resources on economic growth. In contrast, others have found a positive impact, while yet others have found no significant relationship. Each has sought to ask whether resources are on average a curse or a blessing.

Several prominent papers in this literature can illustrate these disparate findings. Gylfason (2001) uses data from 85 countries between 1965-1998 to fit a regression line through a scatterplot, and finds that natural resource "abundance" (measured as the share of each nations's natural capital over national wealth in 1994) is negatively associated with its per capita growth in GDP. In doing so, Gylfason also finds a similar negative result when he tries another resource intensity measure, the share of the primary sector in each nation's total employment. Supporting this finding, Papyrakis and Gerlagh (2004) find that natural resources strongly reduce growth indirectly through their effects on intermediate variables. These indirect effects work through increasing corruption, lowering incentives for

[2] Economic performance is commonly measured using real Gross Domestic Product (GDP) per capita, whether in levels or changes.

investment, reducing openness, worsening a nation's terms of trade and weakening demand side incentives for schooling.

In contrast, some later 'resource curse' researchers have found a positive association between countries' resource production intensity and their economic outcomes, and have expressed skepticism about the original results of Sachs and Warner. Brunnschweiler (2008), for example, estimates a direct positive relationship between natural resource production (specifically mineral and fuel production per capita) and economic growth. Similarly, Brunnschweiler and Bulte (2008) find no significant link between resource dependence (defined as the average of mineral exports as a share of GDP over the period 1970-1989) and growth after using resource abundance measures as instruments, and instead a positive direct association between resource abundance (measured as subsoil wealth) and growth in GDP. A more recent study by Alexeev and Conrad (2011) also finds positive effects on per capita GDP of both resource dependence (measured as value of oil production over GDP) and of resource abundance (estimated oil reserves). Alexeev and Conrad (2009, 2011) similarly find positive effects of oil resources on per capita GDP for the transition economies of formerly socialist countries.

The journey of empirical resource curse analysis begun by Sachs and Warner in 1995 has tended to use macro-country level datasets, especially geared to include low or middle-income countries. Thus, the main empirical approaches have predominantly used cross-country comparisons. For example, Sachs and Warner (1995) used pooled cross-section international data on each country's average annual growth rate between 1971-1990. The same approach was followed by Gylfason (2001), Mehlum, Moene and Torvik (2006) and Papyrakis and Gerlagh (2004). Some researches have used country fixed effects rather than pooled cross sections in order to control for stable, unobserved country-level variables that affect growth (Torvik (2009); Lederman & Maloney (2003)). Some early studies have found an inverse association also holds in country fixed effects analysis (Collier and Goderis, 2009).

Particularly in the late 1990's and early 2000's, when evidence for the resource curse seemed strongest, scholars developed several major causal explanations by which it might operate. These causal channels provided plausible mechanisms through which natural resources could ultimately hamper economic achievement in resource-rich economies.[3] The

[3] Other potential channels for the resource curse that have been identified by others will not be pursued here, such as volatility of commodity prices relative to non-commodity prices.

first channel identified was the “Dutch Disease”.[4] Sachs and Warner (1995) write that the Dutch Disease can delay growth, because it makes countries rely predominantly on resource exports. It then crowds out the performance of non-resource sector exports, such as the manufacturing sector. Gylfason (2001) adds that natural resource exploitation crowds out human capital accumulation by reducing the incentive for young people to remain in school when high paying low skill jobs in the resource sector are on offer. A third possible causal channel of the resource curse is that dependency on natural resources can decrease the quality of a country’s institutions, resulting in a weakening of economic outcomes. Some scholars such as Ross (2001) and Isham, et al. (2005) find that resource intensity can put downward pressure on institutional quality by providing governments with sources of revenue outside income taxes, and thus lessen their need for democratic accountability, and their vulnerability to demands for democratic reforms. Institutional effects are also supported empirically by Bulte, Damania and Deacon (2005) who link resource abundance (measured as a share of resource exports in total exports) with less rule of law and less government effectiveness as evidenced by a corruption measure.

As mentioned, studies looking for a resource curse have now been conducted for over two decades, and have found various conclusions, and raised an extensive debate. As studies have accumulated, some economists have surveyed the literature, and mapped some important conclusions. For example, Cust and Poelhekke (2015), Badeeb, Lean and Clark (2017), and van der Ploeg and Poelhekke (2016) have documented that an inverse association between resource *dependence* (rather than abundance) and economic performance has commonly been found in cross-country macro-level studies. Some survey papers have blamed the literature’s contradictory findings on weak robustness checks, unobserved heterogeneity across countries that affects their economic outcomes, and the possible endogeneity of many commonly used resource dependence measures.

For example, van der Ploeg and Poelhekke (2016) criticize past cross-section and panel data analysis between countries. Firstly, van der Ploeg and Poelhekke claim that international datasets on which most studies depend are commonly too diverse with respect to the characteristic of each country. Employing cross-country analyses can lead to serious omitted

[4] Initially, this label came from the discovery of natural gas near the town of Groningen in 1956, which raised the real exchange rate of the Netherlands.

variable bias issues.[5] Second, they argue that endogeneity problems likely occur when researchers use common proxies for resource dependence such as the share of primary exports in total GDP. As a result, the actual effects of unmeasured factors on growth are wrongly loaded onto resource dependence, or there can be spurious negative correlation with outcome measures.

In their conclusion, van der Ploeg and Poelhekke recommend researchers pursue new strategies and datasets to produce more reliable evidence regarding the resource curse. Especially relevant here, they suggest that within-country analysis which emphasizes a specific area in one country, or the local impact of resource intensity, may provide a more reliable test of the resource curse hypothesis. This recommendation has also been proposed in other recent surveys by Papyrakis (2016), Fleming, et al. (2015), Aragón, Chuhan-Pole, and Land (2015), Cust and Poelhekke (2015). Papyrakis, for example, notes with approval that attention currently has shifted to analysis of data within countries at the district or county level to test the effects of natural resources. Papyrakis then argues that it is not enough to monitor macroeconomic outcomes, but that evidence of resource effects should be evident at the regional level. Further impetus for within country analysis is given by Aragón, Chuhan-Pole, and Land (2015), who emphasize the need to monitor local effects as many resource-rich countries have decentralised their fiscal systems. This decentralisation has in some cases led to significant revenue windfalls for producer regions.

Many academics who have followed this advice have found a beneficial, rather than detrimental effect of resource intensity. Among within-country studies, for example, Caselli and Michaels (2013) assess the effect of resource windfalls at the local level in Brazil, and find a positive impact on incomes, local public goods, and public service delivery. A similar study of mining activities in 71 local government areas in Australia between 2006 and 2007 by Hajkowicz, Heyenga and Moffat (2011) finds no negative effects on per capita GDP. Rather, Hajkowicz, Heyenga and Moffat find that mining operations are positively correlated with income, as well as with selected quality of life indicators. The same conclusion is reached by Fan, Fang and Park (2012) in the case of local level mining in China. Lastly, McMahon and Moreira (2014) also find no evidence of the resource curse when investigating the impact of the mining sector on social and economic development indicators in the five

[5] They suggests that doing “old cross-country” analysis should be no longer be chosen as a way to find evidence of the resource curse. See van der Ploeg & Poelhekke (2016).

resource-rich mining countries of Chile, Ghana, Indonesia, Peru, and South Africa. McMahon and Moreira focused on these five nations because they have a history of substantial mining discoveries.[6]

Unfortunately, such within-country studies have not resolved the resource curse debate. Other within-country studies have found opposing results more in line with those of Sachs and Warner. Papyrakis and Gerlagh (2007), for instance, examine United States counties as a pooled cross section and find a negative cross-county association between resource dependence (measured as the share of the primary sector in the real gross state product (GSP)), and long-term income growth. Papyrakis and Gerlagh also claim that a resource curse can be found even in more homogenous sub-samples of counties. Similarly, James & Aadland (2011) confirm this view and find a negative effect of natural resources earnings on growth in income per capita in counties of the United States. These results are consistent with those of Douglas and Walker (2016) who find negative effects of resource-sector dependence when trying to investigate the effect of coal mining among Appalachian counties in the United States. Douglas and Walker use a panel data set between 1970-2010 which is averaged over every 10 year period, or with four decade observations. Along with using fixed effects in their first analysis, these authors also use two-step GMM instrumental variables to address potential endogeneity in their resource measure.

Surprisingly, while numerous empirical resource curse studies have been carried out in the Middle East, Africa, and Latin America, this phenomenon has not been examined to nearly the same degree in Southeast Asia. Indonesia is the richest country in Southeast Asia in terms of natural resource endowments of all types (oil, natural gas, coal, minerals, forest products, and agriculture).[7] Yet resource abundance and dependence vary dramatically among regions of the country. Some prominent papers have included Indonesia as a sample country among other resource-rich countries (e.g. Gylfason (2001), Gylfason and Zoega (2006), Brunnschweiller and Bulte (2008), Arezki and van der Ploeg (2011)). However, there have been very few studies testing for a resource curse within Indonesia.

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[6] In this study McMahon and Moreira concentrate on low and middle income mining countries and find that mining has a strong positive impact on economic growth and on the Human Development Index (HDI). Unfortunately, the paper does not employ econometric analysis and therefore can not offer proof about any causal effects of mining revenues.
[7] Indonesia is currently 7th in total mineral production, and the largest coal exporter in the world in terms of value added or in government revenues generated by mining.

In pioneering work, Komarulzaman and Alisjahbana (2006) analyze the effect of resource rents (separated as forest, mining, oil and gas, and total resource rents) on the growth rate of district GDP, called real GRDP (Gross Regional Domestic Product) in 2001, the first year of Indonesia's fiscal decentralisation. Edwards (2016) expands the investigation within Indonesia by focusing on the effect of mining dependence (the share of mining in total value-added) on several social development indicators (that include health and education), using cross-section data from the year 2009. However both studies have relied on single year cross-section data, making their conclusions vulnerable to omitted variable bias. More recently, Cust and Rusli (2016) have provided a valuable analysis of the effects of district government revenues associated with petroleum royalties on district economic performance, proxied again by GRDP. Cust and Rusli's method seems to be promising as they have access to a longer period, 1999-2009, and consider effects of royalties on levels and changes in GRDP. Cust and Rusli also address the potential endogeneity of royalty revenues using total offshore oil and gas production as an instrumental variable in both level and change models. Dependence of local government revenues from petroleum royalties is, like most resource dependence or abundance measures, prone to endogeneity because of omitted variables that affect incomes or growth and because of spurious negative correlation where higher incomes simultaneously raise the dependent variable and the denominator of the resource measure. Cust and Rusli emphasize the importance of addressing the endogeneity issue that resource curse researchers face. Surprisingly, far from a resource curse, Cust and Rusli instead find that revenue windfalls boost local economic GRDP. Beyond these few papers, to the best of my knowledge, none has investigated the resource curse within Indonesia using sub-national data.

2.1.2 The Significance of the Research

The limited number of studies of the resource curse in Indonesia motivates me to test whether a curse phenomenon really exists when we can follow Indonesian districts over time. Therefore, this first part of my dissertation attempts to investigate empirically the overall effect of natural resources on economic performance within Indonesia at the sub-provincial level of districts. For reasons of data availability, I focus here on all non-renewable "point source" resources, namely oil, natural gas and coal. I focus on two kinds of resource dependence measures, either the share of resources in district GRDP, or the share of 'windfall' revenues that district governments receive as a share of their total budgets. I consider the years following the implementation of fiscal decentralisation, from 2005 to 2015. Finally, I construct and exploit various instrumental variables for resource dependence by introducing "historical resource abundance" measures available 30 years prior to decentralisation.

As mentioned above, I focus on mining in Indonesia, employing the main resource intensity variables of "mining dependence" and "mining revenue dependence" on sub-provincial level economic performance across all districts in Indonesia.[8] I consider the post-decentralisation period of the Indonesian economy, where much decision-making power and revenues devolved from the central government to provinces and districts. According to the Indonesian Ministry of Home Affairs, in 2015, there were 512 districts within 34 provinces in Indonesia. Since decentralisation began in 2001, the Indonesia government has pursued a policy called "proliferation" or *pemekaran*. This policy has expanded the number of districts continuously. In 2001, there were just 336 districts, rising to 477 in 2010, and 512 in 2015. This proliferation of districts poses some challenges for any local level analysis that follows districts over time.

The rest of this first part of my dissertation will proceed as follows: Section 2.2 reviews the resource curse literature, including both its theories and empirical tests. I pay particular attention to those studies concerned with within-country estimation of resource effects. Section 2.3 emphasizes the historical aspects and the role of natural resources in Indonesia, while Section 2.4 describes the country's substantial policy changes during the period of decentralisation begun in 2001. Section 2.5 explains the data, and my empirical estimation strategies for estimating direct and indirect effects of mining dependence. Section 2.6 discusses the results of my analysis. Finally, Section 2.7 concludes the chapter.

2.2 Literature Review

2.2.1 Natural Resources and Economic Development

Natural resources have been recognized as a key factor in the economic progress of many nations. Walter Rostow (1959) an American economist and political theorist at Columbia University argued that natural resources act as a preliminary foundation for many

[8] Mining here is defined according to International Standard Classification 0509, and comprises natural gas, coal, lignite, crude petroleum and other minerals. The definition follows that used in the recent study by Edwards (2016a). Under its decentralisation scheme, Indonesia has 34 provinces and (in 2015) consists of 512 districts. Since each district publishes information on gross domestic output value [real and nominal price] by sector and in total, I can calculate resource dependence by dividing mining output by total output.

countries' "take off" into industrialisation. Barbier (2005), a development economist, in his book *Natural Resources and Economic Development* argues that this transition phase, "in which countries achieve rapid development", is often driven by access to abundant natural resources, and in particular the discovery of new sources of raw materials. Barbier argues that the term "resource-based development", which has been applied to some well known countries that have been leaders in the world economy, is itself evidence of the influence of natural resource endowments in every stage of economic expansion.

Looking at broad swathes of history, Barbier summarises several phases in which natural resources have contributed to stages of past human civilisation. The first stage, *the agricultural transition*, occured between 8,500 BC to 1 AD, and is characterised as a period when society, either tribes or individuals within society, compete with each other in hunting or planting something on the earth to gain benefit from natural resources, often simply for survival. Barbier calls the second stage, *the era of Malthusian stagnation* (from 1 AD to 1,000 AD); natural resources determined food sufficiency and economic stability in human civilisation. The third stage he calls *the emergence of the world economy,* between 1,000 and 1,500 AD, when international trade in renewable and non-renewable raw materials vastly expanded between nations.

Barbier labels the next historical period *the rise of Western Europe* (between 1500-1913). During this period, many West European countries created colonies in many parts of Africa, Asia and Latin America. These efforts were largely driven by the desire to access quantities of natural resources from these countries and regions. Colonization also occured in North America where two countries, the United States and Canada, became influential in the world economy. Barbier divides this period between *Atlantic economic triangular trade* (between 1500 and 1860), where trade agreements between countries were formalized, and the later *golden age of resource-based development* (from 1870 to 1913).

Wright and Czelusta (2004), who also take a long historical view, argue that a number of successfully developed countries achieved that success with resource based development that was inevitably driven by the influence of natural resources. Wright and Czelusta emphasize the contribution of mineral production, which had strong linkages with advancing technology. Mineral production provided substantial benefits to countries such as the United States and Australia. Doraisami (2015) also argues that substantial knowledge spillovers resulted from the linkages between nations' extractive sectors and industrialisation, which in turn has driven successful development.

The link between natural resources and economic output is commonly approached using a basic Cobb-Douglas technology function in which natural resources are involved as a substantial determinant of a nation's aggregate output.[9] In the growth literature that has developed since Rostow, natural resources are also commonly seen as a part of nation's capital stock K. As one example, Lederman and Maloney (2008) model output assuming that (K) consists of resource endowments, which are used either in static or dynamic growth models.[10]

However, regardless of historians' assertions of a positive effect of natural resources on development, the first empirical study found a famously contrarian result. Sachs and Warner (1995) were the first authors to find empirical evidence for a "resource curse". Empirically, Sachs and Warner find that countries that depended largely on resource exports (measured as the ratio of primary product exports to GDP in 1970) experienced slower economic growth in subsequent periods (measured as the average of 1971-1989). Several causal channels have been proposed to explain why an abundance of natural resources can become a curse (or a blessing) for a society. I concentrate here on four channels that have received dominant attention in many papers: (1) a Dutch disease; (2) effects on human capital, (3) effects on institutional quality, and, (4) effects on the quality of government investment/spending. These will be explored in depth in Chapter 3, but I will give here a short summary.

The Dutch disease was first introduced in the *Economist* magazine inspired by the discovery of natural gas in Groningen, the Netherlands in the late 1950's (Frankel, 2010). As documented by Davis (1995), the resulting explosion of mining in Gronigen led to an appreciation of the Dutch Guilder, which in turn decreased world demand for the Dutch export of non-resource tradable sectors such as manufacturing and agriculture. This

[9] Stiglitz (1974) includes the rate of natural resources utilisation in the form of Cobb-Douglas technology, $Q = F(K, L, R, t) = K^{\alpha_1} L^{\alpha_2} R^{\alpha_3} e^{\gamma t}, \quad \alpha_1 + \alpha_2 + \alpha_3 = 1$. Here Q is a nation's aggregate output, R is its rate of use of natural resources, L represents its supply of labour, and K and γ stand for its capital stock and rate of technological progress, respectively.

[10] For a brief explanation see Lederman and Maloney (2008).

phenomenon was one of the first causal explanations for resource endowments bringing a curse, rather than a blessing.[11]

The next causal mechanism for a curse is through education. Gylfason (2001) and Gylfason and Zoega (2006) have pointed out that natural resource dependence may reduce demand side incentives for human capital accumulation. This may be observed as a decrease in school enrollment, public expenditures on education, or expected years of schooling in more resource intensive societies (Gylfason, Herbertsson and Zoega, 1999). Yet conversely, resource revenues could increase state funding for the supply of public education.

Third, most empirical studies also predict that a resource curse is a phenomenon closely related to institutional quality. There are two variants of this argument: (a) Institutional quality is an endogenous factor, negatively affected by resource abundance/dependence, which in turn worsens economic performance. (b) Institutional quality is assumed to be exogenous to resource intensity, but that quality largely determines whether resources are a curse or blessing.[12]

The fourth channel relates to the quality of public spending that results from resource vs non-resource sources of government revenues. A curse could result if windfall government revenues would be less likely to be spent on investment than non-resource revenues, such as income or consumption tax revenues. This argument often interacts with decentralisation of revenues and responsibility for public good investment and provision, such as that which has taken place in Indonesia.

Under decentralisation, resource extraction activities operate in local areas and the revenues are managed by the central government. However, the central government transfers resource rents back to the producing districts. Cust and Poelhekke (2015) and Aragón, Chuhan-Pole, and Land (2015) both emphasize this link between resource effects, government funding source, and quality of expenditures.

2.2.2 The Resource Curse: A Survey of Empirical Studies

Sachs and Warner's influential study brought much attention from scholars because the authors concluded that resource-rich economies experience slower economic growth than

[11] Aragón, Chuhan-Pole and Land (2015) comment that the Dutch disease is analogous to deindustrialisation driven by resource windfalls.
[12] Mehlum, Moene, and Torvik (2006) distinguish two alternative types of institutions: "grabber friendly" and "producer friendly".

resource-scarce economies, other things equal. In particular, Sachs and Warner (1995, 1999) find that "resource abundance", which they defined as each country's share of primary exports (SXP) in total GDP, has on average a negative association with average growth in single year or pooled cross-section regressions.

This surprising result was found also by subsequent studies (e.g. Gylfason, 2001; Stijns (2000), Papyrakis & Gerlagh, 2004, Mehlum, Moene & Torvik, 2006). However, other studies began pointing to weaknesses of Sachs and Warner's methods. For example, Brunnschweiller and Bulte (2008) criticize Sachs and Warner's resource "abundance" as actually defining its degree of dependence on resources.[13] Brunnschweiller and Bulte distinguish resource abundance as a country's *stock* of natural resource wealth, whereas resource dependence is the proportion of the *flow* of income that a country receives from natural resources. These authors find that resource abundance is *positively* correlated with economic growth and with institutional quality.[14] More specifically, Brunschweiler and Bulte argue that resource abundance positively affects resource dependence, and that Sachs and Warner's resource *de facto* dependence measure (the ratio of resource exports over GDP) suffers from endogeneity. To address this, Brunnschweiller and Bulte instrument this dependence using averaged *historical openness* to trade between 1950-1969, but still find no evidence that higher dependence lowers economic growth.

Other researchers have taken issue with the possible omitted variable bias of Sachs and Warner's cross-section analysis. Lederman and Maloney (2003) update Sachs and Warner's paper by performing both cross-section and panel fixed effects to compare the results. Their panel regression models find a positive effect of resource dependence on GDP per capita, whereas cross-section models find no significant association. Alexeev and Conrad (2009) also use country fixed effects, and find when using large oil endowments as an abundance measure that resource-rich countries experience higher growth in GDP per capita.

[13] Other authors also expressed doubts about Sachs and Warner's measurement. For example Aleexev and Conrad (2016) tried several other measures of resource abudance such as resource deposits per capita or oil and mining production, and find no adverse effect.

[14] In general there is now a consensus that resource abundance represents the stock under the land of resources deposits or reserves while resource dependence is the flow of natural resources. Thus, natural resource abundance tends to be measured by using "stock" measures of estimated deposits in the ground. As an example, Brunnschweiler and Bulte (2008) use each nation's total amount of sub-soil wealth to measure natural resource abundance.

Yet other researchers argue that Sachs and Warner specifically neglected to control for institutional quality. Mehlum, Moene and Torvik (2006) argue that the curse effect is conditionally driven by the (exogenous) quality of countries' institutions. These authors first show that inferior institutions lead to a curse. Instead of following the rent seeking hypothesis, which treats institutions as endogenously affected by resource dependence, they treat institutional factors exogeneously, but use Sachs and Warner's data.[15] They find that when institutional quality is controlled for within the Sachs and Warner model or interacted with the natural resource dependence measure, the negative effect of dependence on GDP growth vanishes in countries with "producer friendly" institutions, while remaining for countries with "grabber friendly" institutions.

Other researchers, such as Arezki and van der Ploeg (2011), take issue specifically with a potential negative spurious correlation that may arise when researchers such as Sachs and Warner place GDP both as the dependent variable, and as the denominator of the right hand side dependence measure. For example, countries experiencing strong non-resource growth would appear to have a negative association between growth in "resource dependence" and in growth in GDP. Van der Ploeg (2011) also notes that cross-section analysis is highly prone to omitted variable bias. Some other recent papers have also tried to focus on dependence measures yet to address potential endogeneity, and again found contrarian positive results. Ouoba (2016) for example, finds positive and significant effects when he tries to use Sachs and Warner's measure: resource dependence in GDP using a sample of resource-rich countries. Ouoba compares results from different techniques such as Driscoll-Kraay Fixed Effects, Instrumental Variables with 2SLS, and a GMM-System estimator following countries between 1980-2010. Similarly, Bjorvatn, Farzanegan and Schneider (2012), using 30 oil-rich countries between 1993-2005 find positive effects of oil revenues on real GDP per capita (in logs).

More recently, Aragón, Chuhan-Pole, and Land (2015) emphasize that it is difficult to generalize the effect of natural resources (positive or negative) at the broad national level. Aragón, Chuhan-Pole, and Land argue that any potential resource curse effect will be a local phenomenon, more suitable to analyze at a local (sub-national) geographic level. In other words, they imply that a resource effect will be difficult to identify using cross-country variation.

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[15] Mehlum and Torvik use Sachs and Warner's data as in Sachs and Warner (1997)

Thus, while most early resource curse tests were cross-country, mixed findings and concerns over omitted variables that affect growth have resulted in a recent shift towards within-country studies. Cust & Poelhekke (2015), Aragón, Chuhan-Pole, and Land (2015) and van der Ploeg & Poelhekke (2016) have all recommended that researchers look for resource effects using within country analysis.[16] Cust and Poelhekke in particular highlight the urgency of narrowing down the investigation of the resource curse to regional development dynamics within specific countries. In a more recent survey article, Badeeb, Lean and Clark (2017) conclude that moving particular attention to within country studies and using more recent data after 2000 is crucial as many resource curse studies have been based on data from the 1990's, with limited variation in resource price movements.

However, even within the confines of within-country analysis, different results still occur, which makes it difficult to reach a general consensus regarding whether resource dependence is a curse or a blessing. For example, Douglas and Walker (2016) conduct an analysis on the effects of coal dependence at the county level in the Appalachian region of the United States. Douglas and Walker use the period 1970 – 2010 for their analysis, and estimate that an increase of coal mining dependence lowers the annual growth rate of per capita income by roughly 0.5-1.0 percentage points in the long run, and by 0.2 percentage points in the short run. Douglas and Walker thus seem to confirm Sachs and Warner's cross-country findings. Guo, Zheng and Song (2016) similarly find negative, albeit weak linkages between resource dependence and output using panel data at the provincial level in China. In contrast, other within-country studies find positive effects of resource dependence, such as Hajkowich, Heyenga and Moffat (2011) and Fleming and Measham (2015) for Australia, Weber (2012, 2014) for Western U.S. states, Libman (2013) for Russia, Aragón and Rud (2013) for the case of Northern Peru, and most relevant for our purposes, Cust and Rusli (2016) for Indonesia (see Appendix 2.4 for a summary of some blessing effect results).

Weber (2012, 2014), for example, focuses on the South-Central United States, and maps 362 non-metropolitan counties in Arkansas, Lousiana, Oklahoma, and Texas, and finds that natural gas development (defined as the change in natural gas production in billions of cubic feet) has a positive effect on total employment, using a first difference method. Specifically, Weber finds that each gas-related mining job is likely to create 1.4 non-mining

[16] Explicitly, these authors accept that within-country studies provide a better identification strategy, Also add that a positive impact on growth has been found by those within-country studies previously done. (Cust and Poelhekke (2015), Aragón, Chuhan-Pole and Land (2015))

jobs for the local area. Boyce and Emery (2011) also find a positive effect when regressing the share of people employed in natural resource industries on income levels using US state level data.

To summarise, the standard resource curse hypothesis has postulated that countries endowed with abundant natural resources grow slower than countries without such endowments. However, empirical findings have been mixed, and striking counter examples exist.

2.2.3 The Resource Curse in Asia and Southeast Asia

Very few empirical studies have tried to examine the effect of natural resources on per capita income in Southeast Asia.[17] A greater number have examined the resource curse in East Asia, in China in particular (see Fan, Fang and Park (2012); Lei, Cui & Pan (2013); Wu & Lei (2016), Zhuang and Zhang (2016)). These do not tend to find strong evidence of a curse using sub-national data (e.g. Fan, Fang and Park (2012) using city level data).

For Southeast Asia as a whole, Sovacool (2010) examines evidence for the resource curse by quantifying some key indicators without using econometrics analysis, and draws the opposite conclusion from a resource curse prediction. He chooses thirteen dimensions of outcome variables to represent all aspects of development, arguing that a single indicator such as economic growth (in GDP per capita) is inadequate to capture complex relationships between resource intensity and development.

Specifically, Sovacool combines six economic factors (gross domestic product, exports, government revenues, per capita income, inflation and poverty levels), political factors (including measures of transparency and natural gas and oil production), and four social indicators (rates of literacy, infant mortality, undernourishment, and life expectancy). Sovacool concludes that Southeast Asian countries, with the exception of Myanmar, are able to avoid the curse. Even the more resource dependent countries achieve good progress in most indicators. By comparing outcomes against those of major Middle Eastern oil and gas

[17] This comprises of ten countries that are currently playing an important role in the world economy. Indonesia, Thailand, Malaysia, Singapore, Cambodia, Vietnam, Myanmar, Lao PDR and Brunei Darussalam.

countries, who are members of OPEC, Sovacool finds that Southeast Asia has performed much better.

In similarly descriptive work, Coxhead (2007) identifies Indonesia, Malaysia and Thailand as resource abundant countries that managed their economies very well between 1975-2001. The average rate of GDP growth in these three countries was above the overall mean of all countries in Southeast Asia. Coxhead argues that a massive flow of foreign direct investment (FDI) between 1985 and 1991 was the key factor which raised industrialisation rates for these three countries. As a consequence of this remarkable achievement, the World Bank has grouped these countries as a new "East Asian miracle" alongside Singapore and some other Northeast Asian economies.

2.2.4 Empirical Evidence Related to the Resource Curse in Indonesia

Moving to Indonesia in particular, there have been only a small number of empirical studies looking within that country, even though many cross-country studies have included Indonesia as a resource-intensive data point.

A few studies have discussed Indonesia and the resource curse in a very descriptive way, such as Usui (1997), Rosser (2007), and Chandra (2012). Usui (1997) claims that Indonesia has successfully escaped relatively unscathed from both the Dutch disease in times of rising oil prices and from later declining oil prices, over the combined period from the 1980's to the 2000's. Usui argues that good policy adjustments have contributed to this. Similarly, Gylfason (2001a) places Indonesia alongside Bostwana, Malaysia and Thailand among 65 countries that have successfully managed long term investment, making their economic growth exceed 4 per cent on average between 1970-1998. Gylfason argues generally that diversification and industrialisation have helped them reach that level of growth.

Rosser (2007), similarly, describes Indonesia's economy during a period of intermittent oil booms between 1967-2000. Qualitatively, Rosser argues that the oil booms did not carry Indonesia into "curse" conditions. Instead, the country experienced strong growth in the 1970's and 1980's in a more sustained pattern than other Southeast Asian countries. Rosser credits this growth in part to political factors such as a successful transition of power (from the old order, under Soekarno's rule (1945-1966), to Soeharto's new order (1966-1998)), and to favourable external economic conditions. Again taking a descriptive approach, di John

(2011) identifies Mexico and Indonesia alone among the ten largest oil exporters as having succesfully managed their growth during oil price booms by introducing a “Dual track strategy”. These two countries translated oil windfalls between 1981-2002 into domestic investment to build and accelerate industrialisation.

Finally among descriptive works, Chandra (2012) considers the effects of oil price booms on Indonesia’s overall economic growth over a longer period. Chandra finds that Indonesia, especially in the 1970’s-1980’s successfully managed the revenue windfall that came from massive mineral exports, especially oil and gas, to build their manufacturing sector. By the 1990’s, much of the overall growth nationally was driven by manufacturing performance, though in the 2000’s it was driven by growth in both the primary and manufacturing sectors. Chandra also notes that although Indonesia experienced oil price volatility in the early 1980’s, the country did not suffer a resource curse generally, nor a Dutch disease in particular. Instead, Indonesia was able to use revenue windfalls to develop their manufacturing sector. By the time of declining global commodity prices in the 2000’s, falling windfall revenues did not much affect the industrialisation process. However, although Chandra’s study is fairly comprehensive in the time period it considers, it is purely descriptive, and only considers overall macroeconomic conditions.

While previous studies have generally argued that Indonesia has avoided a resource curse, few have looked for evidence of resource intensity effects within the country, using district level data, in the period following decentralisation. Prior to decentralisation, during the Soeharto era, Indonesia experienced good progress in terms of key macro-economic indicators. However, the authoritarian governance under Soeharto, while sometimes good for political stability, hampered democracy and increased scope for rent-seeking behaviour among the elites with ties to the government. When the Asian Financial Crisis struck several Southeast Asian countries in 1997, Indonesia’s economy performed particularly badly, making Soeharto step down and paving the way for a change from a highly centralized administration to a decentralised and democratically accountable system of provincial and district level governance.[18]

[18] In the post Soeharto era, Indonesia adopted a decentralisation system, with legal changes beginning in 2001, and political implementation beginning in 2005.

Under decentralisation, all provinces and districts receive a certain amount of revenue based on a legal scheme of “resource revenue-sharing”.[19] In general, the higher the revenues generated from resource endowments within a district, the higher the revenues it receives back into its budget every year. The revenue-sharing schemes known as “intergovernmental transfers” in Law 33/2004, are calculated based on percentage allocations (see Table 2.1).

Hill, Resosudarmo and Vidyattama (2008) were the first researchers to rigorously evaluate Indonesia’s development progress at the provincial level over three decades from 1980-2010. They cover the years before and after decentralisation of funds and decision making to provinces and districts. Although still at the somewhat broad provincial level, which can contain strong variation in district government performance, Hill et al. find some indication that income growth in Indonesia was relatively strong and stable over this thirty year period. They also find that those provinces situated on the islands of Kalimantan and Sumatra were consistently among the richest (proxied by per capita GRDP) and their relative standing remained unchanged between 1999 and 2011.

The first econometric analysis of the resource curse in Indonesia was conducted by Komarulzaman and Alisjahbana (2006). These authors use about 300 districts that existed in 2001. Komarulzaman and Alisjahbana consider the effects of four measures of natural resource rents, measured using district-level resource revenues: (i) forestry revenue; (ii) mining revenue (land rents and royalties from coal and other minerals); (iii) oil and gas revenue; and (iv) total resource revenues (total rent). They find that while total revenue (from all natural resources) has no significant impact on regional economic growth, mining sector revenues are negatively associated with economic growth on average. However, Komarulzaman and Alisjahbana’s study is based on a single year cross section analysis, in the earliest period of decentralisation when many districts had not long been receiving resource funds.

Edwards (2016a) offers more recent evidence regarding Indonesia’s natural resources, albeit not exactly as a resource curse investigation (i.e. not using per capita GDP levels or growth as a dependent variable). Instead, Edwards performs cross-section analysis of more

[19] Aragón, Chuhan-Pole and Land (2015) explain that fiscal decentralisation arrangements provide policies to answer three questions: (1) who should collect revenues (local, regional, or national governments)?; (2) how will resource revenues be shared?; and (3) how these institutional arrangements affect economic performance.

than 430 local districts in Indonesia in 2009, looking at the effect of mining dependence, (proxied using all types of non-renewable resource output over total output at the district level), on various important development indicators. Interestingly when using mining share in GRDP (in log form), Edwards concludes that mining dependence may significantly reduce household human capital investment (measured using education and health expenditures). Mining dependence may also reduce education and health outcomes, which are proxied using senior secondary school enrollment, senior test scores, and births attended by a skilled health worker, respectively. However, Edwards does not use instrumental variables to address potential endogeneity in his resource dependence measure.

Edwards' findings may provide initial evidence of a resource curse within Indonesia. However, similar to Komarulzaman and Alisjahbana, Edwards' analysis covers a single year (2009), and focuses only on social development indicators (health and education). Conversely, Komarulzaman and Alisjahbana's study has the advantage of considering economic performance as a dependent variable, but their study does not follow districts over the period when decentralisation of revenues to districts and political decentralisation to local citizens were fully implemented. To sum up, there is as yet no clear evidence regarding whether heavy reliance upon resources consitutes a blessing or curse for Indonesia.

The study closest to my own investigation is by Cust and Rusli (2016). Cust and Rusli examine the effects of oil and gas dependence on levels or growth in Indonesian district GRDP per capita between 1999 and 2009. Cust and Rusli also address the potential endogeneity of their oil and gas dependence variable by using the instrument of physical offshore oil production (within 0 – 4 miles of the coastline). Taking this more comprehensive approach, Cust and Rusli find a surprising positive, statistically significant effect of oil and gas dependence upon district GRDP using either levels or changes between 1999 and 2009.

While Cust and Rusli's study provides the highest quality investigation of the resource curse within Indonesia to date, my current investigation contributes on several fronts. First, I start my analysis several years later, when district level data reporting capacity had improved post-decentralisation, and I extend analysis to more recent years – 2015. Second, I examine the effects of coal dependence as well as oil and gas. Third, while repeating Cust and Rusli's use of physical output instruments, I also source other instruments related to historical resource abundance – a necessary precondition for resource dependence.

2.3 A Glimpse of Indonesia's Natural Resources

2.3.1 Historical Natural Resources Exploration and Production

Indonesia has a very long history of natural resource exploration. Many ventures were initiated by Dutch geologists, when the Netherlands colonized Indonesia on behalf of the *Netherlands East Indies* company. The petroleum history of Indonesia began in 1871 when Jan Reerink, a Dutch geologist surveyed and drilled at several locations in Tjibodas (now Cirebon district) in West Java Province in search of crude oil. Though Reerink eventually found oil, Tjibodas failed to provide sufficient quantities of production to be commercialized. While Reerink and others made further attempts in some nominated areas, these also were unsuccessful in extracting substantial amounts of oil. Nonetheless, these efforts left some legacies as a clue to the location of oil deposits in West Java and others islands in Indonesia.[20]

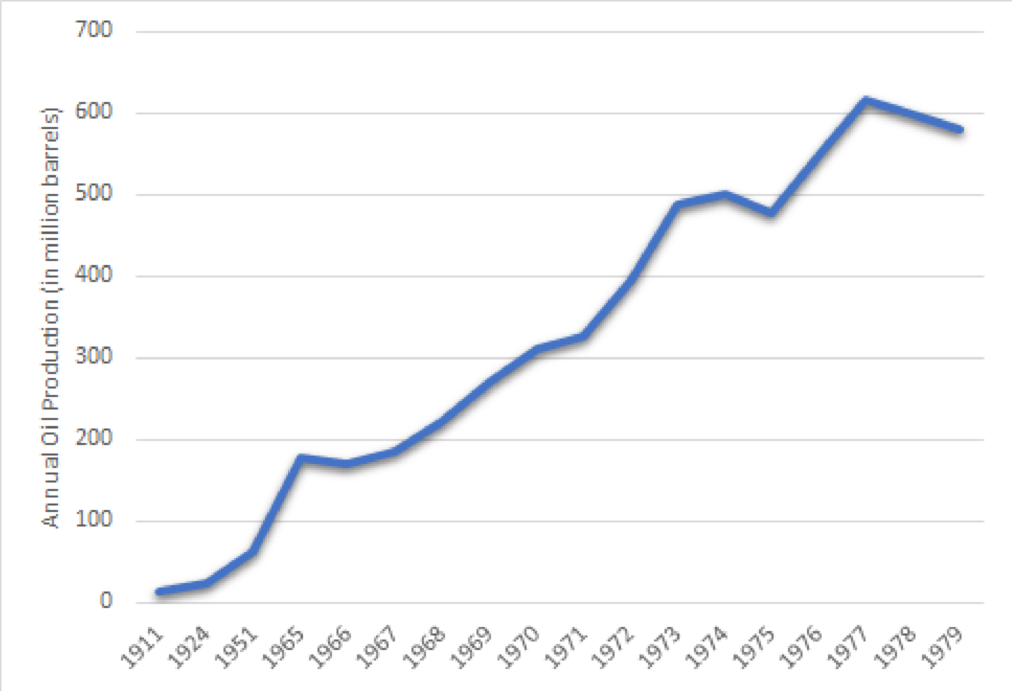
In 1911, the well known Dutch company Royal Dutch (also known as *Bataafsche Petroleum Maatschappij* or B.P.M.) found strong evidence of large deposits of crude oil on several islands. As a result, Royal Dutch secured roughly 44 concessions of oil fields, spread over Sumatra, Kalimantan and Java Islands, which succeeded in producing around 13 million barrels. The *Nederlandsche Koloniale Petroleum Maatscappij* (N.K.P.M) then began exploration in 1912 as a competitor to Royal Dutch, but its concession was limited to operating in the Talang Akar area of South Sumatra so that its production was limited. By 1930, the main fields of oil on Kalimantan Island contributed about 68 per cent of Indonesia total oil production. More specifically, East Kalimantan and North-East Kalimantan Provinces were the largest contributors by the late 1920's.

Caltex, a merger between *Nederlandsche Pacific Petroleum Maatschappij* (a subsidiary of Standard Oil of California) and the Texas Corporation operated in Indonesia starting in 1936. Caltex made many succesful explorations and commercialisation of oil production. Its exploration was concentrated in the Minas Field of Central Sumatra, and by 1940 wells there were contributing about 61.5 million barrels annually (Bee, 1982). Unfortunately, oil production fluctuated and fell dramatically because of the Second World War. Indonesia was targeted by Japan for occupation in large part because of the country's vast deposits of natural resources. Many Dutch concessions were overtaken by the Japanese. At the war's end when Japan surrendered to the United States in August 1945, the young Indonesian leader Soekarno took the opportunity to proclaim Indonesia's independence,

[20] The historical perspective here heavily cites from Bee (1982).

though the Dutch government did not acknowledge Indonesia's proclamation. It failed, however, to regain the country using aggression or political negotiation.

Figure 2.1. Historical Crude Oil Production in Indonesia, 1911-1979



Source: Bee (1982)

During Soekarno's rule of Indonesia, the country adapted a policy of nationalisation of the oil and gas sector. The Indonesia Oil Company took what had been left by Royal Dutch (BPM), Shell, and other companies. Under the Indonesia Oil Company, the rate of production rose from 63 million barrels in 1951 to about 177 million barrels by 1965. However, a coup attempt by the Communist Party in 1965 destabilized the goverment. Soekarno was accused of protecting communist ideology, lost his power, and his old order of government collapsed. Major General Soeharto, who had been supported by the Indonesian military, became the new leader in 1966, and ruled Indonesia until 1998. While authoritarian, the political situation stabilized, and foreign investment was encouraged as a result of a liberalisation policy pursued by Soeharto's cabinet.

The renamed National Oil Company (PERTAMINA) attracted many foreign oil companies to join under "production sharing contracts" to explore and produce crude oil. This strategy was chosen both to share the cost of exploration, and to gain from foreign companies their capital and experience with advanced technology. As a result, many oil discoveries took place beginning in 1968, and resulted in several offshore oil fields, such as Cinta (North-West

Java) and Attakka (East Kalimantan), along with the onshore Minas field in Central Sumatra. Crude oil production thus increased sharply in Indonesia between 1960-1980 (see Figure 2.1). While less prominent than oil, natural gas extraction also climbed rapidly in Indonesia, starting in 1976. The Arun and Badak fields in the Aceh Utara and Kutai districts, contributed to commercializing Indonesia's natural gas production for export across the world (Bee, 1982).

While crude oil has been the dominant non-renewable resource exploited in Indonesia, coal mining also has a long history. Initially, in the 1850's, geologists of the Dutch colonial government struggled to find coal abundant areas, with little attention paid thereafter. But after Soeharto ruled, coal exploration expanded quickly in the late 1970's, driven by the falling price of oil. Following this momentum, an important coal deposit was found in South Sumatra Basin (in the Tanjung Enim and West Banko districts) between 1973-1980, under the supervision of the state owned mining company *PN Tambang Batu Bara*.[21] Following this discovery, a golden period of coal extraction began between 1981-1988. This accelerated after the Indonesian government again invited several foreign companies who had successfully found the deposit, to sign a mining contract known as the first generation of Coal Contracts of Work (CCoW). Much of the country's subsequent coal production was sourced from these locations. In particular, those contracts signed between 1981 and 1990 contributed more than 50 per cent of total coal output in 2015. All contracts were located on Kalimantan Island (in East and South Kalimantan Provinces) and in West Sumatra Provinces ((Leeuwen (1994) and Friederich and Leeuwen (2017)).[22]

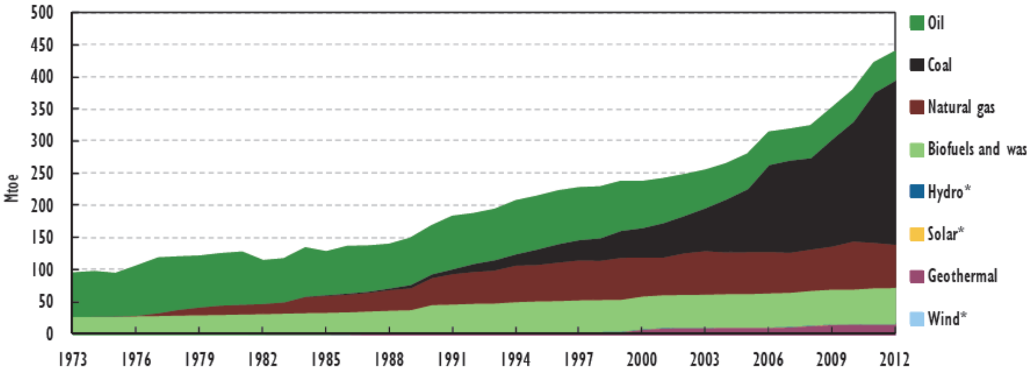
Moving to the more recent development of Indonesia's natural resources, Figure 2.2 shows the production of all types of natural resources in Indonesia over the 1973-2012 period. As shown, oil and coal have comprised more than 60 per cent of total natural resource production in Indonesia. Crude oil, as already indicated, has been a major contributor to Indonesia's resource economy from the 1970's to the 2000's but it subsequently experienced a slight decline relative to coal following the rising world price of coal. As a result, oil remains the largest contributor to mining production in Indonesia, but coal production has risen dramatically to become the second largest resource contributor. Curiously, even though

[21] These historical locations of oil, gas and coal in Indonesia have become the main areas of mineral extraction up to the present time. Kalimantan and Sumatra are the main locations.

[22] There were eleven foreign companies under contract with the Indonesia government under PN Tambang: Arutmin, Utah Indonesia, Agip, Kaltim Prima Cola, Adaro, Kideco, Berau, Chung Hua, Allied Indo Coal, Multi Harapan Utama, Tanito Harum, and Indominco Mandiri (Friederich and Leeuwen, 2017).

natural gas has been extracted since 1976, its production has remained below 100 Mtoe over the 1976-2012 period. Growth in natural gas extraction has thus been very slow.

Figure 2.2. Energy production by source, 1973-2012



Source: IEA, Indonesia Energy Policies (2015, p.21.)
(https://www.iea.org/publications/freepublications/publication/Indonesia_IDR.pdf)

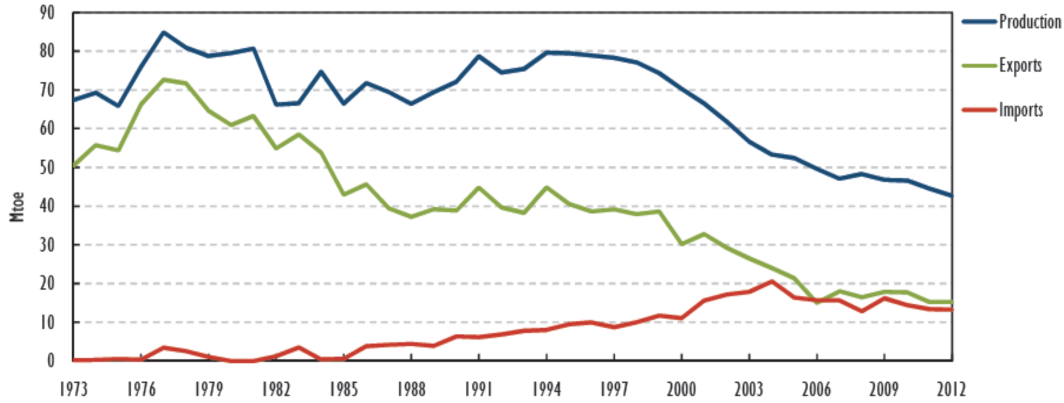
Most recently, however, the production of natural gas has increased rapidly after the Indonesia government in 2009 launched a conversion program from kerosene to LPG (Liquified Petroleum Gas). Finally, the remaining types of resources aside from oil, gas and coal have not contributed very much.

While the production of crude oil has been large on average (as shown in Figure 2.3), annual production and exports rose from 1973-1976, cycled and then declined in a second phase from the mid 1990's to 2012. Production peaked about 80 Mtoe (one million tonnes of oil equivalent) in 1994, before declining subsequently. This decline has been attributed to an excess global supply of crude oil, and a weakening demand for crude oil within European and Asian countries. Another factor has been the rise in LPG use, and to a lesser extent, attempts to develop non-carbon energy sources such as biofuels, geothermal, and hydro.

Export trends followed those in production, with a more pronounced decline since 1976, accompanied by an increase in the level of oil imports. Indeed imports reached the level of exports from 2003 to 2012.

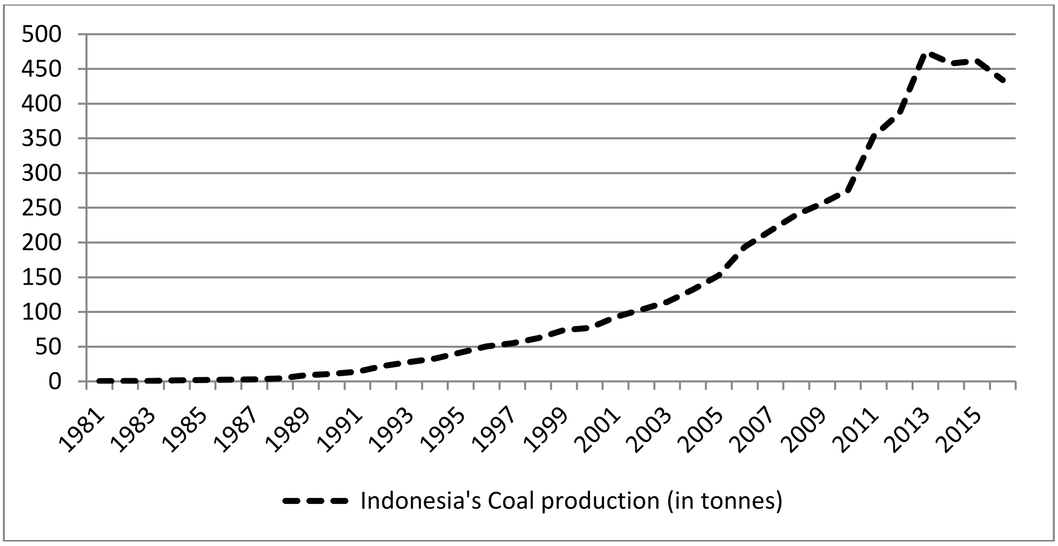
In contrast to oil, a rapid expansion of coal production occured in 1989 and continued until 2013 before appearing to go down slightly in 2014 and 2015 (see Figure 2.4). This rapid

Figure 2.3. Production of crude oil in Indonesia, with export and import trend information, 1973-2012



Notes: Mtoe = million tonnes of oil-equivalent, Source: IEA, Indonesia Energy Policies (2015, p.56.)

Figure 2.4. Production of coal in Indonesia, 1981-2016

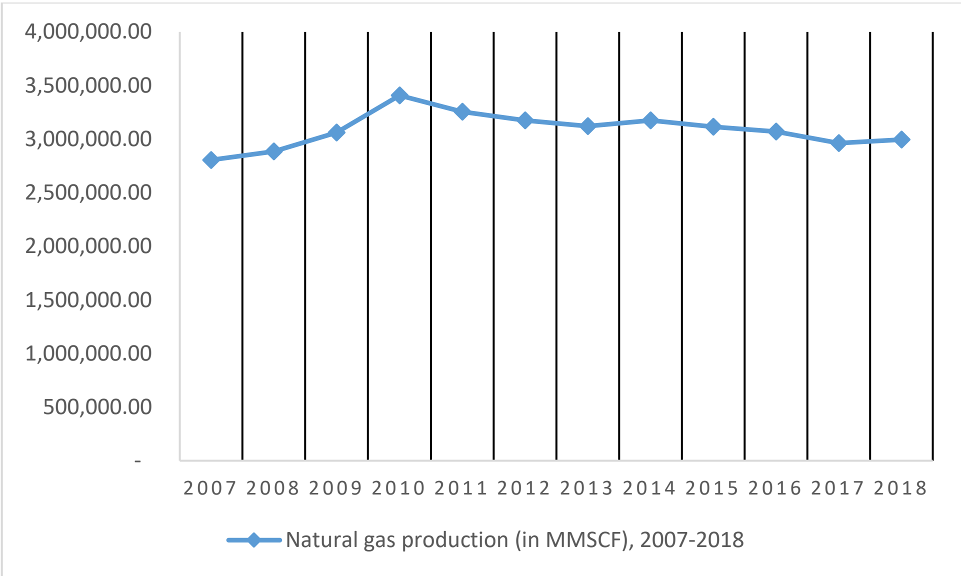


Source: BP Statistical Review of World Energy

expansion has been driven by the high global demand for coal in China, India, and in some parts of Europe. As explained in Section 2.3, coal deposits were concentrated mostly in Kalimantan and Sumatra Islands where now East Kalimantan and South Sumatra Provinces have become the largest extraction areas. The major coal companies have operated in these areas for more than 25 years.

While natural gas was developed in the same period in which oil extraction expanded and commercialized, its production remained stable over time. As shown in Figure 2.5, the level of natural gas production has fluctuated but never exceeded 3.5 TSCF,with the average of about 3.1 TSCF, before decreasing slightly between 2011 and 2018. According to the Ministry of Energy and Mineral Resources, with only those natural gas reserves already identified (142.72 TSCF), current natural gas extraction levels will still be feasible 49 years from now.

Figure 2.5. Production of natural gas in Indonesia, 2007 - 2018



Notes: unit is MMSCF (Million Standard Cubit Feet)
Source: Handbook of Energy and Economic Statistics of Indonesia, 2007 - 2018

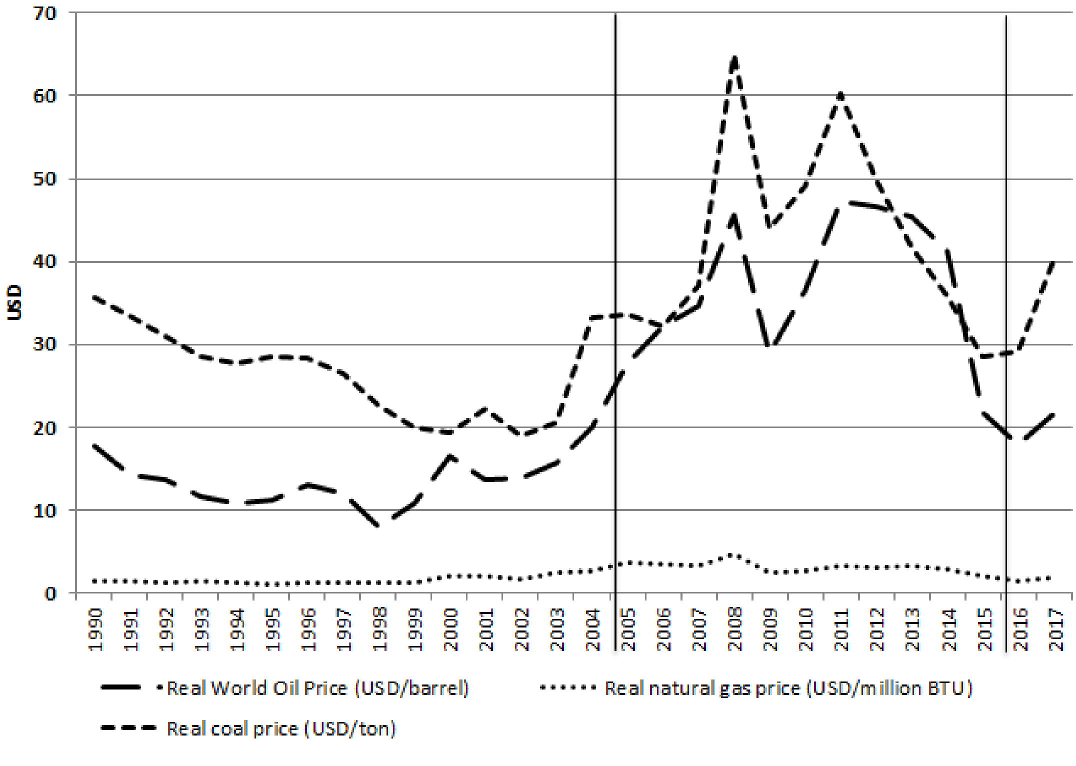
2.3.2 World Energy Prices

One could reasonably argue that the effect of a district's resource dependence on its economic growth might depend on exogenous movements in world prices for oil, coal and gas during the period being studied. I thus present world energy prices in United States dollars for the years surrounding and including my study period: 1990 – 2017. I convert nominal world prices to real prices using the United States' Consumer Price Index. Of particular interest is whether the years of my study (2005 to 2015), which already coincide with the years of fully implemented decentralisation, are also years of atypically rising or falling prices.

Figure 2.6 presents the real prices movements of these three categories. Beginning with oil, it is clear from the Figure that there has not been a steady upward or downward trend in crude prices between 2005 and 2015. Prices rose and fell sharply twice during this period, ending US$5.85/barrel lower in 2015 than in 2005. Nevertheless, relative to the 1990-2004 period, there has been an upward trend in the average price for crude oil.

Moving to coal, the pattern of price movements has been similar to that of crude oil, though more pronounced. In particular, coal's repeated price rise and fall between 2005 and 2015 has been more pronounced that that for oil, while its longer term rise relative to the 1990-2004 period has also been greater than that for oil. Coal prices on world markets have been heavily influenced by China's demand. As China has gradually committed to reducing carbon coal consumption, this has affected global coal prices. Finally, in contrast to crude oil and coal prices, world natural gas prices have remained relatively low and stable over the wider period considered, though still slightly higher in 2005 – 2015 relative to 1990 – 2004.

Figure 2.6. Real World Energy Prices, 1990-2017



Notes: World oil prices are based on spot crude prices (i.e. Brent and West Texas Intermediate (WTI)), while prices for coal are averaged from the Nortwest Europe marker price and China Qinhuangdao spot price. All prices are deflated by the US Consumer Price Index. *Source of data*: BP Statistical Review of World Energy. Link: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

From the price movements of Figure 2.6 we may conclude first that our period of study contains both substantial price rises and falls, but second that it contains prices that were higher on average than those in the preceding 15 year period. This suggests the importance of including a control for time trends in subsequent analysis.

2.4 Overview of the Natural Resource Policy Before and After the Decentralisation Period

Indonesia is the third most populous country in the world after China and India. In Southeast Asia, according to data from the Association of Southeast Asian Nations (ASEAN)[23], Indonesia is the largest in terms of total land area (1,913,579 square kilometres), total population (255,461,700) and gross domestic product (more than 800 US$ million).

Decentralisation began in Indonesia in 1999, when the autonomy law (Law 21/1999) was implemented. Most districts applied by 2001 to be both responsible for public service delivery for their local citizens, and to receive enabling financing from the central government.[24] Outside some more developed districts on Java Island, many districts previously had limited local taxation capacity. Thus, natural resource income became a fundamental source of finance for their spending (Aden (2001)).

Long before decentralisation was implemented, Indonesia's main constitution (Law 1945) adopted a nationalistic and anti-liberalisation ideology. With regards to natural resources management, Article 33 states that: "*The earth and water and the natural resources contained within them are to be controlled by the state and used for the greatest possible prosperity of the people*." However, the new order, under the Soeharto government was far more permissive in welcoming foreign investment, particularly in the extractive sector, and based upon "production sharing contracts". The Indonesian government assumed that these "partnerships" would be mutually beneficial.

Realizing that Indonesia was a large, diverse archipelago country, new government orders under Soeharto (Law 5/1974) sought to minimize the frictions within or between districts and to advance the country's development. Thus under Law 5/1974 the central

[23] Key Selected Indicators data base as announced in August 2016

[24] In 1999, the Indonesian central government initially announced Law 25/1999 regarding revenue sharing with districts from natural resources (oil, natural gas, coal and other minerals, forestry, fisheries resources management). Revenues were first to be collected by the central government and then re-distributed to the local level governments. But the initial regulation was incomplete, and a revised Law 33/2004 was substituted for the previous law.

government fully retained all administrative, political, and fiscal duties, reinforcing Soeharto's authoritarian style of leadership. As explained in the previous section, this relationship changed rapidly in 1999 due to widespread demands for reformation. These changes produced laws that specified how revenue was to be shared, including natural resource revenues.

In essence, under the revised Law 33/2004, revenues from oil and gas wells are allocated to the district in which the *wellhead* has produced oil and gas (defined as 'lifting'). If the wellhead is situated on the district's land it is labelled as an *onshore* location; if it is *offshore*, the nearest distance to the coastline determines the district to which the revenue is allocated. If the distance ranges up to 4 miles, the nearest district has the right to the revenue. If the distance ranges between 4 – 12 miles, the provincial government receives the revenue, while if the distance exceeds 12 miles, the central government retains the revenue. The formula to calculate resource revenues is determined by the realisation of production (*lifting*) of oil and gas.

Thus, oil and natural gas lifting determines how much revenue districts obtain every year from these resources. In contrast, for coal and other minerals, revenues are calculated based upon the total district area in which coal companies have a license to operate, as well as by production volumes and the sales price. These variables are used to formulate *Land rents* and *royalties* as a reference to calculate coal and mineral resource revenue. Whereas land rents are fixed, royalties are paid by the company per unit of production. They can be written as follows:

$$Land\ rents = Total\ Area\ \times Tariff$$

$$Royalties = Sales\ Volume\ \times Tariff\ \times\ Price$$

In summary, the allocation of resource revenues to districts follows strict percentage proportions managed by the Ministry of Finance based upon Law 33/2004. Under these rules, more resource productive districts receive a larger portion of revenues. Table 2.1 summarises the rules for the allocation of revenues from natural resources. Meanwhile, resource-poor or resource-absent districts still receive a windfall, but a much smaller portion. Note that, because of transfer rules between the central and provincial governments, those districts situated within the same province as resource-rich districts may receive higher transfers than similar districts in other provinces without such neighbours. At the extreme, if no resource-rich district exists within a province, a district within it will receive no resource windfall.

Table 2.1. Percentage of Point Source Natural Resources Revenue Sharing Allocation

No	**Type of Natural Resources**	**The Law of 33/2004**		
		Central Government (%)	**Province Government (%)**	**District Government (%)**
1	Oil	85	15* or 15*	
2	Natural gas	70	30* or 30*	
3	Coal and other minerals (Land rents)	20	16	64
4	Coal and other minerals (Royalties)	20	16	32

Source: DJPK Depkeu, Ministry of Finance, Republic of Indonesia (Type of natural resources is restricted only for "point-source" resources type).

*For oil wells 4-12 miles offshore where the 15% is allocated to the province, 5% ultimately goes to the province, and 10% to all districts within that province. For oil wells less than 4 miles offshore, where the 15% is allocated to districts, 3% ultimately goes to their corresponding province, while 12% goes to the district nearest the extraction. For natural gas wells 4-12 miles offshore where the 30% is allocated to the province, 10% ultimately goes to the province and 20% to all districts within the province. For gas wells less than 4 miles offshore, where the 30% is allocated to the district, 6% ultimately goes to their corresponding province, while 24% goes to the district nearest the extraction.

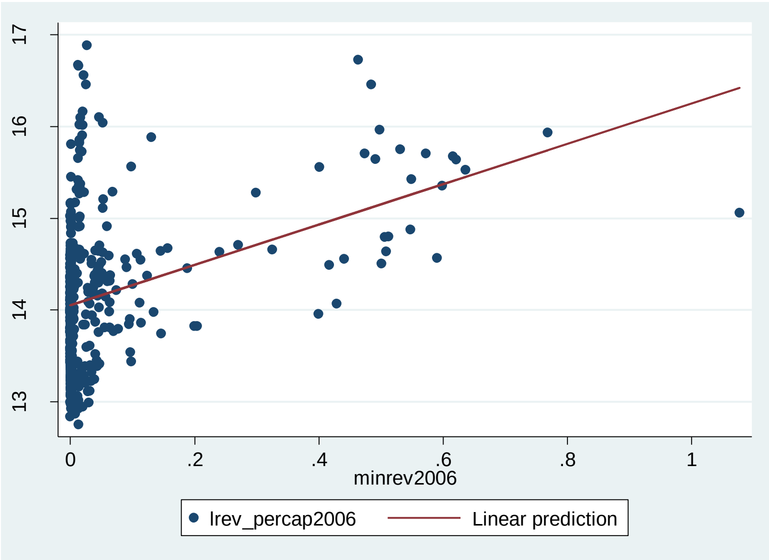
It is important to note that the Indonesian central government makes other grants to districts that may have the effect of partially offsetting district resource windfalls.[25] In particular, the central government also transfers annual development grants for all provinces and districts, quite apart from whether they are resource-rich or not. This transfer, called "the general allocation fund" or DAU, accounts for at least 25% of the national budget each year. Given the limited capability of local governments to generate own-source revenues, the DAU has been a significant source of income to run local government programmes, particularly for under-developed, geographically isolated, or resource poor districts.[26]

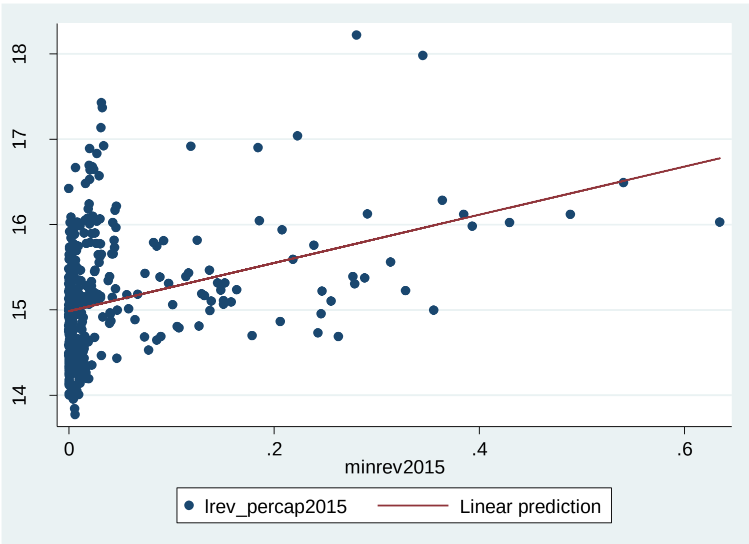
Although DAU funding may lessen the disparity of total revenues available to resource rich and poor districts, it likely remains the case that resource-extracting districts retain on average a revenue advantage over their non-extracting counterparts. To shed light on this, I plot each district's total local government budget per capita in logs (REV_PERCAP), vs. its

[25] In all, district revenue types under decentralisation consist of (1) own-source revenue (2) shared taxes; (3) shared natural resource revenue; (4) DAU; (5) DAK/Special Purpose Grants.
[26] Based on the Ministry of Finance's formulation, DAU funding is substantially influenced by the number of people in poverty, suggesting that poorer districts are likely to receive higher DAU transfers.

share of mining revenues from oil, gas, coal and minerals (MINREV) in district government total budget, both in 2006 and in 2015. Figures 2.7 appears to show a weak positive relationship between the variables involved.

Figure 2.7. Total Revenue Per Capita and Mining Revenues, 2006 and 2015





Source: Author's calculation

2.5 Data and Empirical Estimation Strategy

2.5.1 Scope of Analysis

Indonesia has been repeatedly included among samples of resource-rich economies in cross-country regression analysis. However, little comprehensive analysis has been conducted within the country. This is particularly true in the era following Indonesia’s “decentralisation” of powers to provincial and district levels. This study therefore limits its scope to within Indonesia analysis, following rural districts and urban municipalities over time in the period following decentralisation. Using districts rather than provinces is relevant as Indonesian provinces do not have much administrative authority beyond their role in distributing resources upwards to the central government, or downwards to district.

Indonesia commenced its decentralisation in 2001, and as of 2015 comprised more than 480 districts and municipalities. As explained in Section 2.4, each district obtains and manages revenues generated from resource extraction from the central government based on the proportions stated in Law No. 33/2004. As mentioned, these regulations generally tie distribution to the proportion of resources extracted from each district, so that revenues partially return to the districts where extraction took place. Since 2005, local citizens in each district have also started to elect their regional leaders, both for executive and legislative positions. As a result, districts are quite homogenous in terms of administrative and political processes, and in terms of regulatory background.

2.5.2 Data

Before describing the data and empirical estimation strategy applied in this study, it is necessary to distinguish two types of natural resource concepts used in this study: “resource *dependence*” and "resource *abundance*". I mainly focus on the effects of dependence for two reasons. First, abundance measures, such as estimations of oil and coal deposits, are not generally available at the district level, and certainly not over time as required for panel regression. Abundance measures are available at the provincial level, for some years, but this seems too coarse for within-country analysis for the number of years for which data is available. By contrast, measures of resource dependence based on economic output can be readily constructed at district level. Second, I focus on resource dependence because previous cross-country empirical studies have tended to use such measures, in particular the ratio of resource exports to total GNP or GDP. However, export data at the district level is not available, because records of export values are generally held on behalf of the port from which goods are sent overseas, and not the district of product origin.

Instead, I use a measure of *mining dependence* (which includes coal, oil, gas, and all minerals, including quarrying) similar to what has been employed by within-country papers such as Douglas and Walker (2016) or the closely relevant Indonesian study by Edwards (2016). Edwards employs mining and quarrying's share of total GRDP for each district in Indonesia using cross-sectional data, in 2009. I also use this measure for mining resource dependence in Indonesia, for the years 2005 to 2015.[27]

Some within-country studies have instead tried to capture resource dependence using resource revenues that flow to local governments as royalties, particularly in cases where central governments transfer large portions of revenues sourced from extraction activities back to producing regions. Since this is also the case for Indonesia, I employ additional measures of resource dependence, namely mining revenues (MINREV) defined as total revenues from oil (including natural gas) and coal mining that each district government receives, as a proportion of its revenues from all sources. I also decompose this alternative measure to separate the combined effect of oil and gas from coal revenue dependence, respectively. These data are obtained from several reliable publications by the the Ministry of Finance and the Audit Investigation Board (BPK) of the Republic of Indonesia from 2005 to 2015.[28]

Aside from resource revenue dependence measures, most of the data required for this study come from the "Indonesia Data for Policy and Economic Research" or INDODAPOER data base published by the World Bank.[29] INDODAPOER is a multipurpose dataset providing more than 300 indicators and currently covers the period from 1976 to 2013 at the district

[27] More specifically, 'mining' is defined as an economic activity to extract and prepare for further processing minerals in solid, liquid or gas form. Products include crude oil and natural gas, coal, iron sand, tin concentrate, nickel ore, bauxite, copper concentrate, gold, silver, and manganese. Quarrying, in contrast, is an economic activity that covers extraction of all quarried commodities. These include chemical elements, and mineral and rock sediment below the ground (excluding metal, coal, petroleum, natural gas and radioactive elements). Quarrying commodities include stone, limestone, marble, sand, quartz sand, kaolin, and clay. For a more detailed explanation, see: https://www.bps.go.id/Subjek/view/id/10#subjekViewTab1

[28] The BPK publications can be downloaded using this link: http://www.bpk.go.id/lkpp , while the data from the Ministry of Finance can be accessed by opening the link: http://www.djpk.depkeu.go.id/?page_id=307

[29] The datasets can be downloaded using: http://data.worldbank.org/data-catalog/indonesia-database-for-policy-and-economic-research.

level.[30] INDODAPOER itself gathers information from official government sources, such as Susenas (the National Economic Survey, Republic of Indonesia), from the Indonesia Statistical National Agency (BPS), and from the Ministry of Finance. Unfortunately, most district level observations are missing for most variables prior to decentralisation (1976-2003). Fewer district level observations are missing from 2003 to 2005, and virtually none thereafter. To populate missing observations from 2003 onward, I use the statistical yearbook published by the BPS.[31] The list of variables and their definitions is presented in Appendix 2.1.

Ultimately, I elected to restrict the years of analysis to between 2005 and 2015. I excluded 2003 and 2004 because prior to 2005 there is evidence of some unevenness in the quality of the district level data, due to the political transition to downward democratisation under the decentralisation framework established between 1999 and 2003.[32] There were also some revisions to the fiscal mechanism for revenue sharing for Law 22/1999 concerning regional governments and Law 25/1999 concerning revenue sharing made in 2004 under Law 33/2004. The modifications of this law were announced in 2004, and effectively implemented in 2005. Thus, only by 2005 were both elections and revenue sharing effectively implemented by all districts.[33]

When I try to follow Indonesia's districts over time, an obstacle arises due to a rapid increase in the number of districts after 2005 caused by a "proliferation" policy. As discussed in Section 2.4, Indonesia's central government decentralised their authority to provinces and districts. This was predicated on the view that it is good to make local government closer to the people in order to spur improvements in public service delivery. This policy resulted in the number of districts rising from around 370 in 2003 to more than 500 by 2015. To facilitate longitudinal analysis, I merge "children" districts back into their "parent districts" using the annual population of each child to create weighted averages. Since most districts existing in

[30] I define districts to include rural districts (*kabupaten*) and urban districts (*kota*/municipalities).
[31] This can be freely downloaded from https://bps.go.id/index.php/Publikasi .
[32] Initially, the "big bang" reform of 1999, and approval of Indonesia regional autonomy began in 2001, followed by presidential approval of elections. However, there were challenges to implementation over the first five years as debate escalated over revenue sharing turns, and delays in the implementation of local political elections at the district level.
[33] The number of provinces and districts which perform local elections can be seen here: http://otda.kemendagri.go.id/CMS/Images/SubMenu/Rekap%20Pilkada%202005%20s.d%202014.pdf.

2015 were identifiable from parent districts in 2003, I have chosen this year as a benchmark when aggregating districts back to their earlier forms.

More specifically, I begin with the number of districts in 2015 (including the older and the newer districts). From this complete list, I merge the new districts back to their parent districts down to the districts existing in the year 2003.[34] This results in 390 consolidated districts in 2015, down from 512. While this procedure loses observations for later years, it ensures that no district values are missing during the period 2005-2015, creating a balanced panel.

2.5.3 Estimation Strategy

I use three regression forms to estimate the effects of resource dependence on output: a panel fixed-effects regression following districts in Indonesia, a first-difference regression, and a first-difference regression with instruments to mitigate the potential endogeneity of my resource dependence measures.

2.5.3.1 Model 1: Fixed Effects Estimator

By effectively including a dummy variable for each district, fixed effects models consider the influence of stable but unobserved district characteristics that could be influencing output (Wooldridge, 2016). With 390 districts followed over 11 years, my data are relatively large in the cross section dimension, N, but small in the time-series dimension, T, or a "shallow" panel.

The Fixed Effects (henceforth FE) approach controls for variations *across* districts (i.e. the average of variables between districts) (Wooldridge, 2016). More formally, if the panel regression model is written as: $Y_{it} = \alpha_i + X_{i,t}\,\beta + \varepsilon_{i,t}$, the time-average of each variable can then be written as: $\overline{Y_\iota} = \alpha_i + \bar{X}_i\beta$. If we substract the latter equation in means from the former equation, we get: $Y_{i,t} - \overline{Y_\iota} = \left(X_{i,t} - \overline{X_\iota}\right)\beta + \varepsilon_{i,t}$. As this difference illustrates, fixed effects eliminates the district specific effects α_i caused by unobserved time-invariant heterogeneity between districts.

For FE estimation, I use the following model:

[34] The 2003 list of districts comes from the Ministry of Home Affairs. I excluded the regions of Jakarta (Central Jakarta, West Jakarta, East Jakarta, South Jakarta, Kepulauan Seribu) and Tanjung Pinang district. Jakarta is excluded because it is not defined as a district under decentralisation law. The final district is omitted because of lack of data availability over time.

$$Ln(GRDP)_{i,t} = \alpha_i + RD_{i,t}\beta + X_{i,t}\,\beta + \mu_i + \delta_t + \varepsilon_{it} \quad \text{........................} \quad (1)$$

Here GRDP is per capita Gross Regional Domestic Product (real prices in 2000) of district i at time $t,$ where i = (1, ..., 390), and time t = (2005,….,2015). The natural log of GRDP is used following standard growth models, and is useful for mitigating problems such as potential skewness or non-stationarity that often occurs in annual income panel data that increases over time (Wooldridge, 2016). For example, the log of real GRDP is used in resource curse studies by Al Mamun, et al. (2017), Bjorvatn, et al. (2012), Sarmidi, et al. (2014), and Cust and Rusli (2014, 2016). A final benefit of using logs is that the resulting coefficients on control variables can be easily interpreted as elasticities (if in double-log form). Note that my dependent variable is in levels, which differs from Sachs and Warner, who used average or change in GDP. Note that FE may solve the problem of unobserved district characteristics that affect output, but that it alone does not address potential endogeneity of resource dependence measures. I address this issue subsequently.[35]

To address unobserved heterogeneity, I include $N-1$ district fixed effects represented in (1) by μ_i. I also apply year dummies, δ_t, to control for any shock events common to all districts at a point in time, such as the changes in world commodity prices mentioned previously, business cycle fluctuations, or economic crises. The error term, ε_{it} is assumed to be independently and identically distributed (i.i.d). With year dummies also included, the coefficient on my resource dependence measure will capture the effect of the variation around a district's own average level, but not any effect of differences in average resource dependence across districts.

My key independent variable in (1) is $RD_{i,t}$, the measure of natural resource dependence. As discussed in Section 2.5.2., I try several alternative proxies for this dependence. First, I use the share of overall real mining output in total district real GRDP (MINDEP). A similar measure has been used by Papyrakis and Gerlagh (2007) in the case of the United States, and by Edwards (2016a,b) in the case of Indonesia. Second, I use the share of the district government's revenues that come from overall mining, or oil and gas alone, or coal alone. This approach follows recent sub-national investigations of the effects of resource windfalls associated with resource extraction. For example, resource revenues are transferred

[35] Lederman and Maloney (2008) update Sachs and Warner's seminal work by applying panel data fixed effects. This approach is also followed by Manzano and Rigobon (2001).

on the basis of "producer origin" under decentralisation in Brazil. I thus follow an approach inspired by Casselli and Michaels (2013), Bjorvatn, et al. (2012), and Cust and Rusli (2014, 2016).[36] These measures are respectively labelled as the share of combined oil, gas and coal mining revenues over total district budget revenues (including from offshore and onshore operations) (MINREV), the share of oil and gas revenues over total revenues (OILGASREV), and the share of coal revenues over all revenues (COALREV).

Finally in (1), $X_{i,t}$ is a matrix comprising other determinants of GRDP per capita, such as the total number of annual earthquake events at the district level, the labour force participation rate, and the proportion of households with access to electricity. The latter two variables range from 0-1. Some standard growth variables from cross-country studies, such as openness to trade (export activities) are unfortunately not available within country. Similarly, a variable proxying for private investment is not available at the district level. Positively, government capital expenditures at the district level are available, but will be used in subsequent analysis exploring the the causal channels of resource effects.

Edwards (2016a) argues that mining value-added (i.e. the share of GRDP approach) can be the best practical measure of resource dependence because it captures direct impact. However government revenues from natural resources are also relevant since many rich resource economies re-distribute resource revenues across their counties. It is widely thought that the extent to which countries avoid the resource curse is related to how well they manage revenues generated from resource extraction, and invest it for the benefit of the wider population.

2.5.3.2 Model 2: First-Difference Equation

My second model follows growth research because it allows explanatory variables to have long term effects on either GDP or change in GDP as explained in Barro (1991). To test the impact of the change in resource dependence on the change in income per capita, similar to FE for 2 periods, I use first-difference or FD models to control for unobserved heterogeneity in districts that affects growth (Wooldridge, 2016).[37] Here I take a year

[36] Komarulzaman & Alisjahbana (2006) and Loayza & Rigolini (2016) also use a similar measure of resource dependence. Cust & Poelhekke (2015) discuss the importance of observing the effects of revenue based on natural resources under fiscally decentralised systems.

[37] FD models in resource impact analysis have been used by Weber (2014), Fleming, Measham and Paredes (2015), Lee (2015), Weinstein, and Partridge and Tsvetkova (2018). Fleming et al. (2015) for example regress *ΔLn(Income) = f(ΔlnMiningEmployment, X's)* using 2001 and 2011 as the year interval. FD can

difference, $t_{2015} - t_{2006}$. I retain my earliest available year of 2005 as a baseline year to control for differing initial conditions between districts that can affect their subsequent growth. Controlling for initial GRDP is suggested and commonly implemented in previous resource curse studies (Sachs and Warner, 1995; Douglas and Walker, 2016; Edwards, 2016a).

To see the equivalence between two period fixed effects and first difference models, I follow Wooldridge (2016) and take the difference of panel data across two years, t and $t-1$. Specifically, the first-difference regression can be derived as follows:

$$Y_t = \alpha + \beta X_t + \gamma t + \varepsilon_t \tag{2}$$

$$Y_{t-1} = \alpha + \beta X_{t-1} + \gamma(t-1) + \varepsilon_{t-1} \quad . \tag{3}$$

Subtracting (3) from (2), we get the first difference form:

$$Y_t - Y_{t-1} = \beta(X_t - X_{t-1}) + \gamma(t-(t-1)) + (\varepsilon_t - \varepsilon_{t-1}) \tag{4}$$.

We can also write this as:

$$\Delta Y_t = \beta \Delta X_t + \gamma + \Delta\varepsilon_t \quad , \tag{5}$$

where γ is the time trend and β is the coefficient that has the same meaning as in the original levels model.

Wooldridge cautions that first-difference models can result in large standard errors when estimated using OLS. It is important therefore to use a large cross section, or sufficiently long differences in time (Wooldridge, 2016). Here, I use the longest possible change of 9 years for my first-difference model. However, the downside of this strategy is that it reduces the sample size to effectively that of a single year cross-section model. Notwithstanding this limitation, the first difference model has the advantage of being widely used in the resource curse literature, and of being a good "bridging" model for attempts to deal with potential endogeneity of resource dependence measures using cross sectional instruments.

Applied here my first difference model is:

$$\Delta Ln(GRDP_i) = \gamma + \Delta RD_i\beta + \Delta X'_i\,\sigma + \Delta\varepsilon_{it} \tag{6}$$

capture the cummulative effects of resource dependence throughout the interval concerned while still controlling for unobserved time-invariant heterogeneity.

Here $\Delta Ln(GRDP_i) = ln(GRDP_{i,2015}) - ln(GRDP_{i,2006})$ measures longer term changes in the log of GRDP per capita. The change in GRDP measure follows the growth measure used by Douglas & Walker (2016), Walker (2013), Papyrakis and Gerlagh (2004, 2007), James and James (2011), and James and Aadland (2011) in within-country studies for the United States.[38] The explanatory variable, ΔRD_i, is the change in the level of resource dependence in district i, while γ is the time trend.[39] The $\Delta X'_i$ stands for a set of control variables including changes in labour force participation rate, initial level of population in 2005 (in logs) and the total number of earthquake events over the last 10 years. Initial population is included as a control to test for potential pro-growth effects of economies of scale. Some additional level dummies are included to capture whether districts are urban (a municipality) (DURBAN), and located on Java Island (DJAVA). By including these controls, which would have washed out of annual FE, I can control for the differences between regions of Indonesia. Historically, Indonesian investment and infrastructure development has not been broad based, but more concentrated in Java.

As commonly used in growth models and resource curse studies, I also control for the log of initial GRDP per capita in 2005. In a first difference setting, this variable tests for convergence in GRDP between districts as suggested in traditional growth theory (Barro (1991) and Temple (1999)). A negative coefficient on baseline GRDP would be interpreted as evidence that poorer districts have subsequently had higher growth rates between 2006-2015, catching up to richer districts.

2.5.3.3 Model 3: First-Difference with Instrumental Variables (IV)

Several key resource curse papers criticize the commonly used measures of resource dependence as being very likely to suffer from endogeneity. As it is commonly measured as a ratio, where the denominator captures all economic activities (GDP or GNP) similar to the dependent variable, this measure may not be sufficiently independent, and thus can not be assumed exogenous. One way to address potential endogeneity is to find valid instruments

[38] Douglas and Walker (2016) and Walker (2013) measure the difference in log per capita income over 10 year periods as: $GRDP_{i,t} = \left(\frac{1}{10}\right)(LnGRDP_{i,t,2015} - LnGRDP_{i,t,2005})$. Other authors mentioned above use the formula as: $G^i = \left(\frac{1}{T}\right) \ln \left({Y_T^i}/{Y_0^i}\right)$.

[39] As an alternative, I try regressing the change in per capita income on the level of resource dependence in 2006 and the other determinants as above. The findings are reported in Appendix 2.2. As this model does not control for unobserved factors that are a major concern in the resource curse literature, the FD model in equation (6) will be my main specification.

for resource dependence. In my first difference model, I treat the ΔRD_i variable as potentially endogenous, and seek a suitable instrument for it. I do not use an instrument in my annual panel model because my main instrument is time invariant.[40]

Theoretically, a valid instrument must be correlated with the potentially endogenous regressor in the first-stage regression, and must not be correlated with the error term. In sourcing potential instruments, I follow the strategies of Edwards (2016a) in an international cross-country context, Caselli and Michaels (2013) in the case of Brazil, and Cust and Rusli (2016) in Indonesia. These authors all use an instrument of past resource abundance, and this strategy fits well with the nature of the resource dependence measure that I use in this analysis.

In particular, Edwards has instrumented the ratio of mining to total GDP in 2005 with international estimated fuel reserves in 1971 when using his international dataset.[41] Similarly, Caselli and Michaels instrument for government oil revenues (at municipality level) using oil output in Brazil, while Cust and Rusli use past offshore oil and gas production in Indonesia. All of these approaches seem likely to generate instruments that are correlated with subsequent resource dependence, because abundance is a logical pre-condition needed for production and dependence on resources. Cust and Rusli specifically use a change form for their instruments (the change in physical offshore oil and gas production between 1999 and 2009) for Indonesia. However, their concern is with the effects of oil and gas, not coal mining. It is important to capture coal mining because this resource in particular experienced a boom in Indonesia in the early 2000's.

Following Edwards, Caselli and Michael, and Cust and Rusli, in my third model, I instrument for ΔRD_i using each district's historical level of resource abundance, RA_{1970s} . I try both continous and binary versions of abundance levels based on merging historical maps of natural resources in Indonesia with district level maps as of 2003. For the binary instrument versions, I classify districts as "oil/gas abundant" if they had at least one proven major field as of the 1970's, and as "coal abundant" if at least 20 per cent of the district was covered by "first contract" agreements with coal companies as of the 1980's. For the continous

[40] I do not pursue using the lag of the dependent variable in annual panel models (known as a dynamic panel model using System GMM). I do not use this method because it may introduce a bias, which could lead to wrong inference under the null hypothesis significance test (Bellemare, Masaki and Pepinsky, 2015).
[41] Edwards also regresses mining contribution on various development indicators at district level in Indonesia in 2009. However Edwards does not apply instrumental variables.

instrument versions, for oil and gas I use the number of major or minor oil and gas fields in the 1970's.[42] For coal I divide coal deposit areas by total district areas according to first generation coal agreement contracts in the 1980's as shown in an original map by Leeuwen (1994) and Frederich and Leeuwen (2017). See Table 2.2 for a summary of these instruments.

My historical abundance level instruments are produced using original historical maps released by Bee (1982), Leeuwen (1994) and Friederich & Leeuwen (2017). ArcGIS software was used to match geographic coordinates of oil/gas fields or coal exploration agreement areas according to the Bee, Leeuwen, and Frederich and Leeuwen maps with specific district boundaries as of 2003. This matching procedure resulted in new maps as illustrated in Appendices 2 and 3 of Hilmawan & Clark (2019). These new maps enable me to exploit historical information regarding oil, natural gas, and coal mining abundance as of the 1970's (for oil and gas) or the 1980's (for coal). By this time, knowledge of resource locations had accumulated based in part on exploration efforts by the Dutch when Indonesia was a colony. Yet this period also immediately preceeded a "golden era" of natural resource commercialisation in Indonesia.[43]

While abundance is a logical pre-condition for dependence, the *ex ante* grounds for expecting correlation between *change* in dependence and levels of abundance seems weaker. Consequently, I also try to construct a change form of an instrument. This is difficult to do since it requires a reliable measure of resource endowment, deposit or reserve at district level over the two years of 2015 and 2006. Since such data is not publicly available from the Indonesian government, I follow the approach of Caselli and Michaels (2013) and of Cust and Rusli (2016) in using an instrument based on changes in levels of physical oil and gas output. Note that physical resource output functions less as a logical pre-requisite for resource dependence, than a simultaneous correlate of resource dependence.[44] Data on oil and gas

[42] For coastal oil fields in particular, I only consider onshore and offshore oil and gas wells, within 4 miles from the coastline of the related districts as laid out under Law 33/2004 of the Republic of Indonesia.
[43] One might argue that measurable resource abundance is not actually exogenous to income, since poorer regions might invest less in oil, coal or gas exploration. However, as I have described, historical exploration in Indonesia was funded centrally either by Dutch geologists, or the Indonesian central government in conjunction with multinational corporations.
[44] For comparison, I also try using only historical resource abundance measures as instruments for ΔRD_i. With fewer instruments, tests for overidentification cannot be run for two of four resource dependence measures (OILGASREV or COALREV), and Kleibergen F tests indicate greater weakness. I find that the estimated effects of resource dependence on growth remain very similar to those reported below. In particular, the estimated effects of MINDEP, OILGASREV and MINREV remain significant and positive, using continuous or binary form-based instrument (see Table 2.2 below for details about instruments).

lifting are released by the Ministry of Energy and Mineral Resources (MEMR).[45] These data are used as a basis for district revenue redistribution calculations. With regard to coal dependence, I use instead Rupiah measures of land rents summed with royalties as an instrument.[46] With these change instruments, ΔOil_i and $\Delta Coal_i$ constructed over 9 year differences (2015 minus 2006), the first stage regression can be constructed.

Returning to my third model, the first difference specification can initially be expressed as follows:

$$\Delta LnGRDP_i = \gamma + \beta_1 \Delta RD_i + \Delta X'_i\,\beta_2 + \Delta\varepsilon_{it} \tag{7}$$

With instruments constructed, the first and second stage regressions are modelled as follows:

$$\Delta RD_i = \alpha_0 + \delta_1 RA_{1970s} + \delta_2 \Delta OIL_i + \delta_3 \Delta GAS_i + \delta_4 \Delta COAL_i + \Delta X'_i\,\delta_5 + \Delta\varepsilon_{it} \tag{8}$$

$$\Delta LnGRDP_i = \gamma + \pi_1 \Delta\widehat{RD}_i + \Delta X'_i\,\pi_2 + \Delta\varepsilon_{it} \quad . \tag{9}$$

Thus I treat the change in resource dependence, ΔRD_i, as potentially endogenous and use level measures of resource abundance, RA_{1970s}, and changes in physical resource output, as instruments.[47] When total resource dependence is considered, using either MINDEP or MINREV, I use all instruments together, both in level and in change forms. When resource dependence is measured as oil and natural gas separately from coal, however, I use only a single abundance instrument associated with the particular type of dependence. Why might such positive correlation occur? In the case of oil and gas, the considerable capital and risk bearing needed to ramp up extraction following succesful exploration could lead to a positive correlation. In the case of coal, first contracts only reveal the potential for viable coal deposits to be found, which would require time to confirm with geological sampling.[48]

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[45] In practice, oil and gas lifting data is used under the decentralisation scheme (Law 33/2004), to calculate resource revenue sharing across districts. The same rule also applies for coal, using land rent and royalties as a basis for coal revenue allocation.

[46] The land rents and royalties rely heavily on coal production. Indonesia formulates land rents as a fixed tariff that must be paid by coal producers based on their licenses, whereas they pay royalties per unit of output.

[47] To see how the individual instruments perform in both, I also provide first-stage regressions based on reduced form models as follows: Δ*RD = f(instruments, X variables)* and Δ*lnGRDP = f(instruments, X variables)*. Results are shown in Appendix 2.3. Reassuringly, instruments have consistent signs and significance across the two models. The exceptions are my coal abundance and change in coal output instruments.

[48] By looking at the current main locations map of natural resources extraction activities provided by the Ministry of Energy and Mineral Resources, no dramatic shift occured over the 2006-2015 period. Thus,

Table 2.2. Instrument Summary

	Resource Dependence Measure	**Instruments – historical resource abundance-based (level)**		**Instruments – changes in resource abundance-based**
		Continuous	**Binary**	
ΔRD_i	$\Delta\left(\frac{GRDP_{mining}}{GRDP}\right)$	- Oil + Natural Gas Abundance 1970's	- Oil + Natural Gas Abundance 1970's	- Change in oil production - Change in gas production
		- Coal Abundance 1980's	- Coal Abundance 1980's	- Change in coal production
	$\Delta\left(\frac{Revenue_{mining}}{Total\ Revenues}\right)$	- Oil + Natural Gas Abundance 1970's	- Oil + Natural Gas Abundance 1970's	- Change in oil production - Change in gas production
		- Coal Abundance 1980's	- Coal Abundance 1980's	- Change in coal production
	$\Delta\left(\frac{Revenue_{oil+gas}}{Total\ Revenues}\right)$	- Oil + Natural Gas Abundance 1970's	- Oil + Natural Gas Abundance 1970's	- Change in oil production - Change in gas production
	$\Delta\left(\frac{Revenue_{coal+minerals}}{Total\ Revenues}\right)$	- Coal Abundance 1980's	- Coal Abundance 1980's	- Change in coal production

Table 2.2 summarises my various instruments, and how they relate to my various measures of resource dependence. For all instrumental variables estimation, I use two step feasible efficient Generalized Method of Moments (GMM2S) with robust standard errors rather than two stage least squares (2SLS) to address the potential presence of heteroskedasticity and produce more efficient estimates.[49] I then perform diagnostic tests of whether my instruments are sufficiently correlated with resource dependence and sufficiently

there is no way for district governments to experience resource windfalls in 2015 without having successfully proven deposits, 30-40 years before.

[49] I use the ***ivreg2*** command in the STATA module developed by Baum, Schaffer, and Stillman (2007).

uncorrelated with the error term (instrument "exogeneity"). Correlation or relevance can be checked using the Kleibergen-Paap F statistics for the first stage regressions, or the Cragg-Donald Wald (if error terms are assumed to be identically and independently distributed) (Schaffer, Baum and Stillman, 2003; Baum, Schaffer and Stillman, 2007). I use an F statistic > 10 as a rule of thumb following Wooldridge (2016, p.478) to verify instrument strength.[50] Instrument exogeneity will be examined using overidentification tests such as Hansen's *J*-statistic.[51] Overidentifications tests require the number of instruments to exceed the number of suspected endogenous regressors.

2.6 Empirical Results

Summary statistics for annual panel and first-differenced data are shown in Tables 2.3 and 1.4, respectively. My dataset uses 4,290 observations for 390 districts for annual panel specifications and 390 district changes in first-difference models. In annual FE, the average real GRDP per capita (in logs) is 4.13 and the standard deviation is 0.690. The mean share of mining GRDP in total GRDP is about 9.0 per cent, while the share of mining revenue over all district government revenues is about 5.3 per cent.

Figure 2.8 presents a scatterplot of the correlation between real GRDP per capita and mining dependence (MINDEP) as measured by the share of mining over total GRDP. Both variables are an average value for the 11 observations between 2006 and 2015 for each district. As shown, overall, as MINDEP increases, economic performance rises, which implies a positive relationship between income per person and district economic reliance on mining. I also add a linear trendline generated from Excel which shows a positive relationship. Recall here that mining is broadly defined to include oil, gas and coal and other minerals.

[50] Although an F statistic of 10 has traditionally been viewed as a'safe' lower bound, a recent study by Young (2019) indicates that it may be inadequate in the presence of heteroskedasticity. Kleibergen F statistics, however, can be used as a robust statistic when heteroskedasticity, autocorrelation or clustering occurs (see Baum, Schaffer & Stillman, 2007, p.490).

[51] Failure to reject the null hypothesis of the Hansen *J* statistic suggests that instruments satisfy the exogeneity condition. However caution should be raised as this test is a necessary but not sufficient condition for instrument exogeneity. As sufficiency cannot be demonstrated with a statistical test, researchers must also provide sound logical reasoning for why proposed instruments satisfy the exclusion restriction.

Table 2.3. Descriptive statistics for all districts/years pooled

Variable	Obs	Mean	Std. Dev.	Min	Max
Real GRDP per capita (in logs)	4290	4.139	0.690	1.951	7.684
Mining Dependence GRDP	4290	0.091	0.179	0	0.955
Mining Revenue Dependence	4290	0.053	0.124	0	0.872
Oil&gas revenue Dependence	4290	0.038	0.107	0	0.872
Coal Revenue Dependence	4290	0.015	0.044	0	0.550
Earthquake	4290	0.060	0.253	0	3
Labour force participation rate	4290	0.645	0.096	0.195	0.988
Households with electricity	4290	0.874	0.190	0.003	1

Table 2.4. Descriptive Statistics for First Difference Model

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ Real GRDP per capita (in logs)	390	0.414	0.345	-0.852	2.685
ΔMining Dependence	390	0.012	0.142	-0.614	0.795
ΔOilgas Revenue	390	-0.029	0.091	-0.528	0.224
ΔCoal Revenue	390	0.015	0.048	-0.119	0.359
ΔMining Revenue	390	-0.013	0.084	-0.523	0.256
Earthquake	390	0.464	0.936	0	7
ΔLabour force partic.rate	390	0.068	0.112	-0.191	0.443
GRDP per capita, 2005 (in logs)	390	3.937	0.704	1.951	7.684
Population, 2005 (in logs)	390	12.721	1.029	9.450	15.227
DURBAN	390	0.208	0.406	0	1
DJAVA	390	0.303	0.460	0	1
Instruments					
Oilgas_continuous	390	0.154	0.660	0	7
Coal deposit_continuous	390	3.660	14.327	0	94.214
Oilgas_binary	390	0.059	0.236	0	1
Coal deposit_binary	390	0.067	0.250	0	1
Δoil production (thousand barrels)	390	-103.164	3805.166	-22751.3	64381.61
Δgas production (MMBTU)	390	267.544	31094.970	-402891	378035.7
Δ coal production (IDR)	390	92.619	508.369	-45.277	5845.853

Next, Figure 2.9 shows a similar pattern for my second type of resource dependence measure—district government revenues from oil and gas over all sources of revenue. Once again, each observation represents an eleven year average for each district. Here again, a simple regression line through the scatterplot has a positive slope, contrary to a resource curse prediction. In both figures, I also notice the presence of outliers which could have a disproportionate influence on results, and suggest a possible issue with heteroskedasticity. While excluding the outliers may solve the issue of disproportionate influence, it could also eliminate the historical resource-rich districts used as instruments in the first-difference regression.[52] I thus keep the original observation in all specifications, with the caution that the results may be sensitive to their inclusion.

Before moving to regression analysis, I first compare the overall average performance of per capita GRDP growth between Indonesia's resource-rich and resource-poor districts.[53] Using the data I will subsequently use in regressions, I find that resource-rich districts achieve on average higher growth in per capita income than resource-poor districts, with a 8.2 per cent difference in overall growth achieved from 2006 to 2015. A simple t test finds this to be a statistically significant difference at the 1 per cent level.[54]

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[52] As my last chapter will also focus on spatial analysis, dropping a district that is potentially an outlier would also change the configuration of my spatial weigth matrices.

[53] I rank each district for resource dependence based on the value of mining's share in its total GRDP averaged between 2006 and 2015, from the largest share to the lowest. I then split these 390 districts into two different groups (each with 195 observations). While each 195 districts group had a positive average growth: richer and poorer districts grew 45.5 % and 37.3% over the nine years, respectively.

[54] I test these two groups, richer and poorer districts, by first obtaining a pooled value from the sample variances and then finding the t statistic. Manually, calculation of pooled variance uses this formula $S_p^2 = \frac{(n_1-1)S_1^2+(n_2-1)S_2^2}{n_1+n_2-2}$, where n is total observation of the first (x_1) and second group (x_2), and S^2 is the variance of each group. The t statistic value is $t = \frac{(\bar{x}_1-\bar{x}_2)}{\sqrt{S_p^2/n_1+S_p^2/n_2}}$.

Figure 2.8. Mining Dependence and Real GRDP per capita (averaged over time for each district)

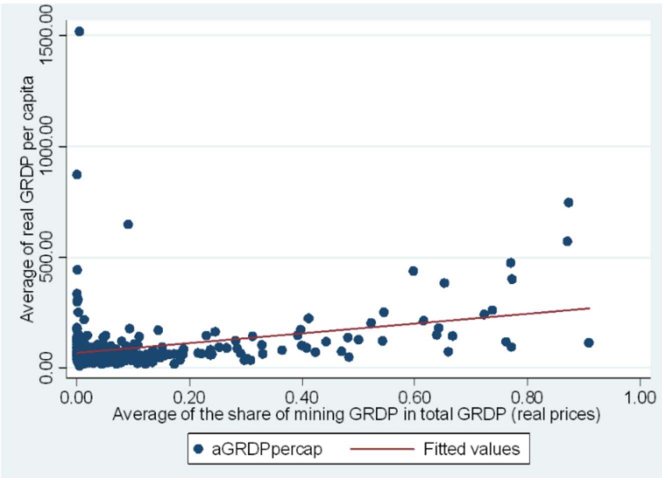
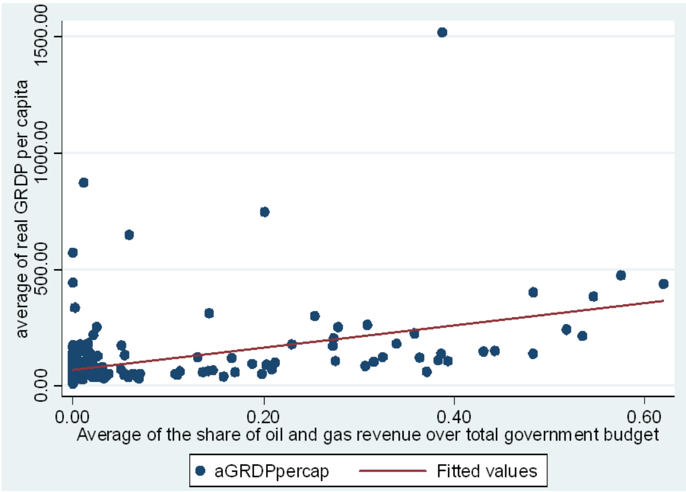


Figure 2.9. Oil and Gas Revenues and Real GRDP per capita (averaged over time for each district)



2.6.1 Annual Panel Data Results

As a baseline, I describe results in Table 2.5 from annual FE regressions at the district level, using the period 2005-2015.[55] Real GRDP per capita (in logs) is used here as the dependent variable. The impact of all four resource dependence measures is presented in models (1) to (4). Similar to the scatterplots, the first model shows a surprising sign according to the standard resource curse hypothesis. I find that mining dependence (shown in model (1)) is positively associated with real GRDP per capita at the local level in fixed effects

[55] Because in subsequent first difference analysis I compare 2006 to 2015 results, I have also run the annual fixed effects analysis using 2006 to 2015 data only. The results are virtually identical. Results are available from the author upon request.

analysis. That is, districts that increase in dependence (measured through mining's share of district GRDP) have larger per capita GRDP, on average. The coefficient on MINDEP in model (1) seems especially strong. Here, a one standard deviation increase in MINDEP (0.179) is associated with an increase in real district income per capita of (0.179*0.406 = 0.0727) 7.27 per cent, on average, all else equal.

Coal resource revenue dependence looks to have a negative effect on GRDP per capita. In contrast, oil and gas dependence has a positive sign but insignificant effect. Thus, combined oil, gas and coal dependence has a coefficient near zero and not statistically significant. At first glance, these results may indicate that resource dependence in overall output is good for GRDP, while dependence in government budgets has either no effect, or possibly a negative effect on GRDP for coal in particular. That is, the resource that comes closest to resource curse predictions is district government coal revenue dependence.

Looking at other control variables in Table 2.5, the frequency of earthquake events appears to be negatively associated with GRDP over time, though only at the 10 per cent level. As the earthquake variable is defined as the annual number that each district experienced between 2005-2015, model (2) finds that one additional earthquake decreases real per capita GRDP by 1.68 per cent (=100(0.0168)). This seems reasonable as the damage from earthquake occurrence reduces economic performance and raises risks of investment in new goods and services, which can lower growth. Other controls, such as the labour force participation rate has a positive coefficient but is insignificant. Surprisingly, the proportion of households with access to electricity is not significantly associated with local GRDP per capita.

Overall, my FE results do not seem to support the standard resource curse hypothesis, with a possible exception for local government dependence on coal mining revenues. They do not support the view that non-renewable resources lead to reduced local GDP. These results are similar to those found by Cust and Rusli (2016) at the district level in Indonesia and in line with some blessing effects found by other researchers as summarised in Appendix 2.4. However, in spite of controlling district fixed effects and year effects, the potential endogeneity of my four resource dependence measures has not been addressed, and I do not have suitable annual instruments to do so.

Table 2.5. Panel Fixed Effect Model of the Effect of Resource Dependence on real GRDP per capita

Dependent Variable: GRDP per capita (in logs)

VARIABLES	(1) FE1	(2) FE2	(3) FE3	(4) FE4
Mining Dependence	0.406***			
	(0.113)			
Oil&Gas Revenue		0.167		
		(0.170)		
Coal revenue			-0.421*	
			(0.241)	
Mining Revenue				0.0353
				(0.132)
Earthquake	-0.016*	-0.016*	-0.017*	-0.017*
	(0.008)	(0.009)	(0.009)	(0.009)
Labour force	0.105	0.117	0.104	0.117
	(0.078)	(0.078)	(0.078)	(0.077)
Household elect.	-0.073	-0.008	-0.005	-0.007
	(0.089)	(0.092)	(0.093)	(0.092)
Constant	3.891***	3.867***	3.879***	3.869***
	(0.075)	(0.076)	(0.076)	(0.076)
Year Effect	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,290	4,290	4,290	4,290
R-squared	0.492	0.478	0.479	0.478
Number of DISTRICT1	390	390	390	390

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Thus, my first assessment using FE models is inconclusive. Therefore I move next to a first-difference model, using 2015 and 2006 as the final and initial years, respectively.

2.6.2 First-Difference Estimates

In the first-difference model (FD hereafter), I include some level dummy variables to capture the urban/rural nature of districts (DURBAN) and potential spatial benefits of being a district in the centrally located island of Java (DJAVA). Note that such unchanging characteristics could not be retained in fixed effects analysis. With a direct measure of urban/rural status, I no longer use household access to electricity, but I still use the sum of earthquakes at district level. As mentioned previously, I now also include initial real GRDP per capita in 2005 (in logs) to control for initial economic conditions, and to test for a convergence in per capita GRDP between initially richer and poorer districts. Additionally, I also control the size of initial district population in 2005 to test for gains to growth from economies of scale.

Table 2.6. Effects of resource dependence on change in real GRDP per capita (in logs) in First Difference form (without instruments)

Dependent Variable: ∆GRDP per capita in logs

VARIABLES	(1)	(2)	(3)	(4)
∆Mining Dependence	0.738***			
	(0.190)			
∆Oilgas Revenue		-0.160		
		(0.473)		
∆Coal Revenue			0.469	
			(0.522)	
∆ Mining Revenue				-0.076
				(0.389)
Earthquake	-0.033**	-0.034***	-0.032***	-0.034***
	(0.013)	(0.012)	(0.012)	(0.012)
∆Labour force partic.rate	0.037	0.025	0.073	0.020
	(0.186)	(0.192)	(0.189)	(0.206)
GRDP per capita, 2005 (in logs)	-0.113***	-0.148***	-0.150***	-0.141***
	(0.032)	(0.037)	(0.034)	(0.029)
Population, 2005 (in logs)	0.008	0.0003	0.004	0.0002
	(0.023)	(0.026)	(0.026)	(0.027)
DURBAN	0.046	0.040	0.047	0.036
	(0.042)	(0.042)	(0.045)	(0.044)
DJAVA	0.085*	0.038	0.036	0.034
	(0.048)	(0.047)	(0.044)	(0.045)
Constant	0.730**	0.983***	0.938***	0.961***
	(0.290)	(0.357)	(0.328)	(0.350)
Observations	390	390	390	390
R-squared	0.164	0.082	0.084	0.081

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.6 reports the effect of changes in mining dependence on changes in longer term real GRDP per capita again using four different measures of resource dependence. As with FE, I find a positive association between rising output dependence and growth. In model (1), a standard deviation increase in the change in mining's share in local GRDP is associated with a (=0.142 * 0.738 = 0.105) 10.5 per cent higher GRDP per capita. As with FE, the effects of government dependence on resource revenues is less conclusive. In model (2), the coefficient on oil and gas revenue dependence is negative, but not statistically significant, while coal effects in model (3) are insignificant but the sign is positive. Therefore, when I aggregate both oil and gas and coal, it too is statistically insignificant (see model (4)). With potential endogeneity of my resource dependence measures not yet addressed, I find evidence that overall resource output dependence is positively associated with growth in real GRDP, and no clear association between government revenue dependence and growth in GRDP.

The impact of earthquake frequency on district economic performance is also similar to that found in FE in all models. Note that for FD models the earthquake variable is defined as a cumulative total of each district's earthquakes over the 10 years (2006-2015). What is new in Table 2.6 is the strong effect on subsequent growth of initial real GRDP per capita (in 2005). The coefficient on baseline GRDP per capita is negative in all four models at the 1 per cent level. My finding here is consistent with convergence of incomes between poorer and richer districts during the decentralisation period.

Among other control variables, the sign of the dummy variable, DURBAN, is positive, though not statistically significant in any specifications. Similar results occur for DJAVA, though with slightly stronger evidence that districts in the historically more developed island of Java look to have grown more rapidly since decentralisation than other districts. In model (1), in particular, Java's districts (excluding the capital Jakarta) grew 8.81 per cent higher between 2006 to 2015 than non-Java districts though the effect is significant only at the 10 % level. [56]

The FD results seem broadly similar to those from FE models with resource dependence in GRDP a blessing, and dependence in government budgets neutral. Nonetheless, the resource dependence findings in these models are not addressing the possible endogeneity of my resource dependence measures. I thus move to results using FD estimation with instrumental variables.

2.6.3 First-Difference Estimates With Instrumental Variables

For my final results, I add two types of instrumental variable (IV) analysis to a FD model, where the relatedness of these instruments was explained in Table 2.2. Table 2.7 provides results using the continuous form of abundance-based instruments along with the physical output instruments. Recall that the instruments are defined as the total number of major and minor petroleum (oil and natural gas) fields, in the 1970's, and the relative share of coal deposit areas to total district areas, in the 1980's. For comparison purposes, I place the earlier OLS results side by side with IV-GMM results.

I start with whether the instruments satisfy the relevance and overidentification tests. In general, the instruments are fairly strong, particularly for oil/gas and coal resource

[56] To interpret dummy explanatory variables when the Y variable is in logs form, I follow the formula 100.[exp$(\widehat{\beta_i}) - 1$] (see Wooldridge, 2016, p.212).

dependence for models (3′)-(4′). As shown, the Kleibergen Paap F statistic ranges from 16.834 in model (1'), to 25.347 in model (3), greater than the recommended rule of thumb for instrument strength. Alternatively, as shown in Table 2.7, according to Cragg-Donald F statistic values, we see relevance increasing from models (1′) and (4′) to (2′) and (3′). However, I emphasise Kleibergen F statistics that are robust in the presence of heteroskedasticity. Likewise, regarding overidentification, the Hansen *J* statistic fails to reject the null hypothesis of exogenous instruments in any models from (1′) to (4′), though with the lowest p-value in model (2') of 0.1486. This implies that my instruments pass the necessary conditions of the two tests, which are consistent with validity.

With the performance of my combined instruments appearing fairly strong for all models, I next test whether the change in resource dependence, ΔRD_i, is endogenous. In model (1′), the p value from a Hausman type endogeneity test cannot reject the null that mining dependence (model (1′)) is exogenous (p value 0.248). However, endogeneity tests reject exogeneity in IV-GMM models (2′) to (3′) at the 5% level, with p values of 0.015 and 0.018, respectively. In model (4′′) the p value is close to borderline, at just above the 10 per cent level (0.108). Therefore, with exogeneity rejected or borderline rejected for 3 of 4 models, I move next to describe second stage IV results.

Just as in the FD case without instruments, I find no evidence that higher non-renewable resource dependence creates an adverse effect on growth. As is clear from models (4'), (1') and (2'), my resource dependence coefficients increase in their magnitudes with use of instruments, and are significant at the 1 per cent or 5 per cent levels. Under the IV-GMM estimator, a change in district government dependence on oil and gas revenues in model (3') has the largest estimated coefficient. Here, an increase of a standard deviation in the change in oil and gas revenue dependence, on average, increases real income per capita by (0.091*1.765 = 0.1606) 16 per cent. This finding once again does not confirm Sachs and Warner's negative findings in a within-country case. Instead, these results support the views of many earlier descriptive papers for Indonesia considering the effect of the oil boom of the 1970's and 1980's (see Gylfason, 2001; Rosser, 2007; Sovacool, 2010).

For its part an increase in coal revenue dependence continues to have no significant effect on long run growth if instruments are included, though the sign of the coefficient turns negative. The insignificant effect of coal may have been caused by the weak performance in individual instruments as shown by the first-stage regression results in both reduced form models. For example, as reported in Appendix 2.3, coal abundance and change in coal production have inconsistent signs in models (5) and (6), when they are respectively regressed on change in the share in coal revenue in total government budget or change in per capita income.

Table 2.7. First difference model of effect of resource dependence on GRDP per capita (CONTINUOUS abundance levels plus change in production IV's)
Dependent Variable: ΔGRDP per capita (in logs)

	(1)	**(1′)**	**(2)**	**(2′)**	**(3)**	**(3′)**	**(4)**	**(4′)**
VARIABLES	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**
ΔMining Dependence	0.738***	1.356***						
	(0.190)	(0.444)						
ΔOilgas Revenue			-0.160	1.765**				
			(0.473)	(0.810)				
ΔCoal Revenue					0.469	-0.696		
					(0.522)	(0.645)		
ΔMining Revenue							-0.076	1.164**
							(0.389)	(0.581)
Earthquake	-0.033**	-0.031*	-0.034***	-0.035***	-0.032***	-0.037***	-0.034***	-0.026**
	(0.013)	(0.018)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)
ΔLabour force partic.rate	0.037	0.059	0.025	0.051	0.073	-0.045	0.020	0.215
	(0.186)	(0.189)	(0.192)	(0.234)	(0.189)	(0.201)	(0.206)	(0.179)
Ln GRDP per capita, 2005	-0.113***	-0.111***	-0.148***	-0.035	-0.150***	-0.119***	-0.141***	-0.097**
	(0.032)	(0.036)	(0.037)	(0.066)	(0.034)	(0.039)	(0.029)	(0.039)
Population, 2005 (in logs)	0.008	0.023	0.000	0.021	0.004	-0.006	0.000	0.032
	(0.023)	(0.020)	(0.026)	(0.026)	(0.026)	(0.025)	(0.027)	(0.021)
DURBAN	0.046	0.075*	0.040	0.012	0.047	0.018	0.036	0.048
	(0.042)	(0.042)	(0.042)	(0.059)	(0.045)	(0.047)	(0.044)	(0.045)
DJAVA	0.085*	0.114*	0.038	-0.048	0.036	0.029	0.034	-0.022
	(0.048)	(0.060)	(0.047)	(0.050)	(0.044)	(0.043)	(0.045)	(0.042)
Constant	0.730**	0.487*	0.983***	0.351	0.938***	0.973***	0.961***	0.397
	(0.290)	(0.282)	(0.357)	(0.323)	(0.328)	(0.320)	(0.350)	(0.256)
Cragg-Donald Wald F stat		8.900		29.017		111.683		27.509
Kleibergen-Paap Wald F		16.834		27.754		25.347		14.807
Hansen *J* statistic, P-value		0.223		0.355		0.635		0.149
Endogeneity test, P value		0.248		0.015		0.018		0.108
Observations	390	390	390	390	390	390	390	390
R-squared	0.164	0.103	0.082	-0.107	0.084	0.065	0.081	-0.001

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The reported negative *R*-squared in column (2') and (4') can be obtained when using IV estimation as the sum of squared (SSR) of residuals exceeds the total sum of squared (TSS) of dependent variable (see Wooldridge (2016), page 471; or https://www.stata.com/support/faqs/statistics/two-stage-least-squares/ for detailed discussion).

Regarding the other control variables, effects are generally similar to the FD model without instruments. For example, the cumulative number of earthquakes over 10 years negatively affects the change in per capita income at district level in Indonesia in all four models of resource dependence. Initial GRDP per capita again has a strong negative association with district income per capita, indicating convergence as before.

Given no evidence of a resource curse with continous abundance level instruments (combined with change in physical production instruments), I next estimate the same models but now using binary abundance level measures, combined with change in physical production measures. As previously described, a binary variable for oil/gas abundance takes on a value of 1 if a district has a major oil field and 0 otherwise; that for coal abundance takes a value of 1 if the district has a proportion of 20 per cent or more with coal deposits, and 0 otherwise. Results are provided in Table 2.8. Kleibergen F statistics indicate that the binary abundance instruments generally are strong for models (4′), (2′) and (3′), with F values of 13.896, 30.976 and 27.580, respectively. More importantly, overidentification test p values are now everywhere far above rejection thresholds in all models. Thus the binary abundance instruments combined with physical production change instruments past tests consistent with validity, albeit still with some weakness in model (1′).

Moving to findings, Table 2.8 shows that results are similar when the binary abundance instruments are used in place of continous ones. The coefficients on resource dependence are positive, and significant for oil/gas and for oil/gas and coal combined. Taking oil and gas revenue dependence as an example in model (2′), a one standard deviation increase in the change of the share of oil and gas revenue over total government revenues is associated with an increase in long run per capita GRDP of about (0.091*1.359 = 0.1236) 12.36 per cent. Once again, with binary instruments as without instruments, there is no significant association between rising coal revenue dependence and per capita income.

In the analagous endogeneity tests using binary abundance instruments, I again find that exogeneity cannot be rejected in model (1′), and can be rejected in model (3′). In contrast, evidence of endogeneity is now stronger in model (2′) rather than borderline (p value 0.063), and weaker in model (3′) (p value 0.167).

Table 2.8. First difference model of effect of resource dependence on GRDP per capita (binary abundance levels plus change in production IV's)

Dependent Variable: ΔGRDP per capita in logs

	(1)	**(1′)**	**(2)**	**(2′)**	**(3)**	**(3′)**	**(4)**	**(4′)**
VARIABLES	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**	**OLS**	**IV-GMM**
ΔMining Dependence	0.738***	1.143**						
	(0.190)	(0.579)						
ΔOilgas Revenue			-0.160	1.359*				
			(0.473)	(0.710)				
ΔCoal Revenue					0.469	-0.456		
					(0.522)	(0.708)		
ΔMining Revenue							-0.076	1.059*
							(0.389)	(0.637)
Earthquake	-0.033**	-0.031*	-0.034***	-0.034***	-0.032***	-0.035***	-0.034***	-0.027**
	(0.013)	(0.018)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
ΔLabour force partic.rate	0.037	0.135	0.025	0.068	0.073	-0.003	0.020	0.237
	(0.186)	(0.186)	(0.192)	(0.218)	(0.189)	(0.202)	(0.206)	(0.173)
Ln GRDP per capita, 2005	-0.113***	-0.108***	-0.148***	-0.056	-0.150***	-0.128***	-0.141***	-0.087**
	(0.032)	(0.035)	(0.037)	(0.056)	(0.034)	(0.038)	(0.029)	(0.039)
Population, 2005 (in logs)	0.008	0.029	0.000	0.020	0.004	0.001	0.000	0.031
	(0.023)	(0.020)	(0.026)	(0.025)	(0.026)	(0.026)	(0.027)	(0.021)
DURBAN	0.046	0.069	0.040	0.019	0.047	0.030	0.036	0.039
	(0.042)	(0.042)	(0.042)	(0.053)	(0.045)	(0.047)	(0.044)	(0.044)
DJAVA	0.085*	0.093	0.038	-0.032	0.036	0.025	0.034	-0.019
	(0.048)	(0.066)	(0.047)	(0.047)	(0.044)	(0.043)	(0.045)	(0.043)
Constant	0.730**	0.415	0.983***	0.430	0.938***	0.919***	0.961***	0.368
	(0.290)	(0.281)	(0.357)	(0.293)	(0.328)	(0.322)	(0.350)	(0.257)
Cragg-Donald Wald F stat		8.108		41.389		115.597		31.065
Kleibergen-Paap Wald F		7.759		30.976		27.580		13.896
Hansen *J* statistic, P-value		0.269		0.456		0.631		0.470
Endogeneity test, P value		0.697		0.018		0.167		0.063
Observations	390	390	390	390	390	390	390	390
R-squared	0.158	0.136	0.075	-0.036	0.077	0.072	0.074	0.012

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Regarding other control variables with binary abundance instruments, earthquake frequency still has negative and statistically significant effects, as I found in the previous results. The coefficient on initial district population level is not significant across models, suggesting no benefits of economies of scale on growth. The initial GRDP per capita in 2005 is statistically significant at the 1 per cent level across all specifications, again implying that convergence is occuring in real income levels between districts during the 2006-2015 period.

Interestingly, although the regression results have generally found that resource dependence is promoting income, the results in Appendix 2.2 which use initial resource dependence in 2006 have reported consistent negative signs and statistically significant at 1 per cent level according to IV-GMM specifications. For example, in column (2′), where the instruments' strength and exogeneity have passed necessary requirements to be valid, a one standard deviation increase in the share of oil and gas revenue in total local government budget in 2006 lowers per capita income by (0.126*(-1.084)=) 0.136 or 13.6 per cent. These findings support resource curse argument as found in many early studies particularly those which relied on data at country level. Across time, however, concerns have raised due to the problem of unobserved time-invariant factors at national level which cannot be solved by putting resource dependence as a level variable in cross-section regressions as tried here. While acknowledging these contrary findings, I therefore put more weight on my first difference specifications with instruments better approach has been used increasingly studies conducted at the local level, though to date mostly in developed country studies.

2.7 Discussion

My estimation results seem generally contrary to the predictions and some findings of the resource curse literature. I find a positive or no significant association between various measures of resource dependence and per capita income, using fixed effects models and first difference models, with and without instruments. With some exception regarding the effects of coal revenue dependence, this lack of negative association persists when I control for relevant growth variables, and control for district and year fixed effects as well as initial income levels (real GRDP per capita) and control for population, labour force participation, and urban/rural status. There is instead some evidence that resource dependence seems to confer a blessing effect, particularly when measured using overall mining's share in GRDP, or in overall or oil/gas revenue dependence. For its part, coal revenue dependence seems to confer a neutral effect, neither a significant blessing nor a curse, lacking statistical significance in almost all specifications in FD models.

Why might resource dependence in output, or in oil and gas revenue dependence, confer benefits for GRDP within Indonesia, when it does not seem to have elsewhere?

Table 2.9. Summary of Results

	(1)	**(2)**	**(3)**	**(4)**
FE	+	◦	◦	–
FD	+	◦	◦	◦
FD with instrument 1	+	+	+	◦
FD with instrument 2	+	+	+	◦

Notes: FE = Fixed Effect; FD = First Difference; Instrument 1 is continuous+changes of physical production; Instrument 2 is binary+changes of physical production;

There are several factors which could contribute: (i) commodity price booms during my sample period, (ii) the effects of Indonesia's decentralisation policy, (i.e. improvements in institutional quality triggered by decentralisation); (iii) the effects of quality of public spending on investments, such as education or infrastructure.

First, the oil boom during the 1970's and 1980's, and the coal boom during the 2000's, have tremendously contributed to Indonesia's non-tax revenues, which even before decentralisation of resource revenues has made growth in per capita income more progressive in the outlying regions of Indonesia. The world crude oil prices have also been on average higher during the period of 2005 – 2016 relative to the preceeding 15 year period, though with substantial fluctuation, suggesting that this may have contributed to resource dependence's pro-growth effects. This also suggests that resource-rich regions, mostly situated in Kalimantan and Sumatra, have enjoyed high incomes because of their historical abundance of natural resources. Far from this income being a "curse", regional dynamic studies of Indonesia have identified most resource-rich regions in Eastern and Southearn Kalimantan and Sumatra Island as consistently being the most prosperous regions according to GRDP per capita between 1999 and 2011 (Hill, Resosudarmo, Vidyattama, 2008; Hill and Vidyattama, 2016). My results support this evidence, and similarly confirm Cust and Rusli's (2016) study that finds that government revenues driven by oil and gas royalties have significantly increased district GRDP.

In particular, as indicated earlier by national level studies of Indonesia such as Usui (1997), Rosser (2007), di John (2011) and Chandra (2012), my results are in line with earlier work showing that Indonesia has avoided a resource curse. These studies argue that Indonesia successfully escaped a Dutch disease or resource curse more broadly during 1973-1985 as a result of managing its oil windfalls to strengthen both its agricultural and manufacturing sectors. Although such "activist" industrial policy interventions have not persisted, they may have benefited resource intensive regions in the years prior to decentralisation.

Second, Indonesia is an archipelago country consisting of five large islands and more than 450 districts. With the implementation of decentralisation, there is scope for considerable variation in regional government policies. Spillover effects from more successful districts, or competition between local leaders, has been implicitly encouraged by the central government through a system of rewards and punishments.[57] To the extent better governance can forestall a resource curse, Indonesia's decentralisation may have contributed by creating incentives for better local governance.

To provide an example, take the fiscal rules implemented since 2005. The mechanism designed to redistribute windfalls across districts may have contributed to expanding the ability of poorer local governments to finance themselves. This could raise local living standards as predicted by Aragón, Chuhan-Pole, and Land (2015), if the revenue streams derived from oil are used to fund local public provision of infrastructure and education. Therefore, if it is true that a key factor to escaping the resource curse is how well a country manages its resource revenues, the incentives of decentralisation for good governance at the local level may explain Indonesia's positive resource outcomes.[58]

In support of this "good governance" explanation, Bostwana is often cited as an example of a country that established an effective system for prudential fiscal policy to manage mining revenues. It is then taken as an example among developing resource-rich countries of a society that has avoided a resource curse (Iimi, 2007). In Indonesia's case, where state corruption has historically been a problem, the central government undertakes

[57] Theoretically, fiscal decentralisation is believed to affect economic growth positively. Fiscal decentralisation may aid growth under the assumption that this system leads to higher economic efficiency because district governments are better placed to provide local public services than central/national government. Furthermore, competition among district governments and the rapid mobility of local citizens may better match the preferences between governments and their local people (Davoodi and Zou, 1998).

[58] For an example of this argument, see *Natural Resource Charter* (Second Edition), (www.resourcegovernance.org and www.naturalresourcecharter.org.)

some efforts to monitor what local governments do. Financial audit investigations, for example, have been conducted annually by the Indonesia Audit Board (BPK) since 2005. The BPK investigates the performance of the central government, including State Owned Enterprises (BUMN), but it also investigates local district local governments on some aspects of quality of their financial reporting. It thus creates accountability incentives even at the local government level. The BPK announces their findings every six months, which has likely contributed to good governance. Similarly, since 2010, the Indonesian Ministry of Home Affairs has annually evaluated all district governments and ranked them based upon their overall performance index.[59]

The period of my analysis, 2005-2015, captures a time when substantive political participation was distributed to districts. It seems likely that this created improvements in public service delivery and accountability through the use of direct local elections. Of course, decentralisation that increases the authority of local goverments could conceivably multiply the incidence of lower-level money politics, corruption, and inefficient allocation of public service delivery. However, local elections and heightened political participation can be a tool to make local citizens more aware of what their government does, which could in turn make resource revenue use more transparent. For example, district governments would find the resource revenues helpful for reaching the goals set for them in the Medium Term Regional Development Plan (*Rencana Pembangunan Jangka Menengah Daerah*(RPJMD)). All levels of government are obliged to show how they fulfill this plan. The contents of these plans are themselves based on campaign promises of the winning parties during election campaigns.

Other researchers also, such as Cust and Poelhekke (2015) and Aragón, Chuhan-Pole, and Land (2015) in their survey paper, emphasize that government spending effects may be responsible for regional growth dynamics. Growth may well be related to how well local governments spend resource revenues. Connecting this assumption to Indonesia’s context, if a district government uses resource revenues to expand their public investment or public spending, this could raise income.

[59] The Ministry of Home Affairs investigates district government performance for most districts. Its ranking of districts is then used to give rewards and punishments. For the researcher, this index can provide a measure of institutional quality. In 2012, the Ministry of Administrative and Bureaucratic Reform also announced The Report of Accountability Performance to stimulate good governance implementation at district level. “Local leader commitment” and “innovation” are two important indicators for determining the highest score. For example, Banyuwangi district has been given an A index and recognized as the best governed district in Indonesia in 2016.

A final explanation why resource dependence may be positively associated with GRDP in Indonesia has to do with education provision. While traditional resource curse explanations have looked at negative effects on demand for education, these have ignored potential positive effects of windfall revenues on the supply side. Some resource-rich economies have avoided curse effects, possibly by using resource windfalls to invest more in education and human capital. In Indonesia's case, better education provision is one of the ultimate goals of public service delivery stated in most RPJMD's. It is possible that districts with resource revenues have used these to boost education and health provision beyond what they would otherwise be, creating gains in subsequent labour productivity.

Overall, the above explanations are still speculative, built from conceptual and empirical findings by studies in other locations. I have not confirmed which causal transmission channels may be responsible for the overall resource blessings found in my first chapter. Thus, to test whether some of these speculations are supported by evidence, I will investigate them more formally in my subsequent chapters.

2.8 Conclusions

So far in my analysis, I have empirically examined the direct effect of resource dependence, proxied by mining's share of GRDP or share in government revenues, on real GRDP per capita. I have examined resource dependence's effects by applying annual Fixed Effects (FE) regressions and a longer term First-Difference (FD) models. Both approaches deal with unobserved heterogeneity across districts that may affect their GRDP. In the FD case, I have also introduced various instruments for my resource dependence measures in case they are endogenous. These instruments have been both in levels (using continuous and binary historical resource abundance measures) and in changes in physical output (oil, natural gas, and coal mining) used.

The original resource curse hypothesis was that having a high dependency on natural resources can lead to poor growth performance. Following Indonesia's districts between 2005-2015, I find little support for this hypothesis. Instead, I find that in most specifications, non-coal natural resource dependence is positively associated with local district income, particularly when it is measured as mining's share of GRDP.

2.9 Appendices

Appendix 2.1. Definition of Variables and Data Sources

Variable	Definition	Source
Real GRDP per capita	Natural logarithm of the GRDP (Real Gross Regional Domestic Product) divided by total population at district level	INDO DAPOER World Bank, The Indonesian National Statistical Agency (BPS)
Earthquake	The number of earthquake events at the district level	Indonesian National Board for Disaster Management (BNPB). Can be accessed online here: http://dibi.bnpb.go.id/dibi/
Labour force participation rate	Natural logarithm of the participation of labour force in the number of people at working age (15-65)	INDO DAPOER World Bank, BPS
LGRDP per capita ‘05	Natural logarithm of initial GRDP percapita in 2005	INDO DAPOER World Bank, BPS
LPOP_05	Natural logarithm of initial population in 2005	BPS
DURBAN	Dummy urban status (municipalities) = 1 if urban districts, = 0 if non-urban/rural district	Identity of urban district/municipality is taken from the Ministry of Home Affairs, the Republic of Indonesia
DJAVA	Dummy of Java Island = 1 if the districts are located on Java Island, = 0 otherwise	-
Household electricity	Per centage of households with an access to electricity.	INDO DAPOER World Bank
MINDEP	The ratio of mining GRDP to total GRDP (real)	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
MINREV	The share of mining revenues, summing oil, natural gas, and coal revenues, in total government budget at district level	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS

Variable	Definition	Source
OILGASREV	The share of oil and natural gas revenues in total government budget, at district level	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
COALREV	The share of coal and other minerals revenues in total government budget, at district level	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
OILGAS BINARY	Dummy variable, = 1 if at least one major oil or gas field operated there during 1970’s, = 0 otherwise.	Ooi Jin Bee (1982)
COAL BINARY	Dummy variable, =1 if at least 20% of district is covered by a “first generation” coal agreement contract during the 1970’s, = 0 otherwise.	Leeuwen (1994); Friederich & Leeuwen (2017)
OILGAS CONTINOUS	The number of major and minor oil and gas fields in 1970’s production period in all island in Indonesia. Major oil and natural gas fields is weigted by 1, and all minor fields are weighted by 0.25. So, if in district A has a 10 minor oil/gas fields location, therefore: $District_A = 10 \times 0.25 = 2.5$	Ooi Jin Bee (1982)
COAL CONTINOUS	The share of coal deposit areas (showed by first generation coal agreement contract introduced by Leeuwen (1994, 2017)) of total area of respective district.	Leeuwen (1994), Friederich & Leeuwen (2017)
ΔGRDP PER CAPITA	The natural logarithm of difference of real GRDP per capita, formulated as: $\Delta\text{GRDP per capita} = ln\left(\frac{GRDP_{percapita,2015}}{GRDP_{percapita,2006}}\right)$	INDO DAPOER World Bank, BPS
ΔMINING DEPENDENCE	The difference of mining dependence between 2015 and 2006, formulated as: $(MINDEP_{2015}) - (MINDEP_{2006})$	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia

Variable	Definition	Source
ΔMINING REVENUE	The difference in mining revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔOILGAS REVENUE	The difference in oil and gas revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔCOAL REVENUE	The difference in coal revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔLABOUR FORCE PARTIC.RATE	The change in labour force participation rate between 2015 and 2006	INDO DAPOER World Bank, BPS
ΔPOPULATION (LOGS)	The change in the population (in logs) between 2015 and 2006	INDO DAPOER World Bank, BPS
Δ COAL PRODUCTION	The change in coal land rents and royalties between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia
ΔOIL PRODUCTION	The change in oil production (in barrels) between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia
ΔGAS PRODUCTION	The change in natural gas production (in MMBTU) between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia

Appendix 2.2. Results based on the regressions of the change in log income per capita on initial resource dependence

	OLS				IV-GMM			
	(1)	(2)	(3)	(4)	(1')	(2')	(3')	(4')
VARIABLES	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	miningrev
Mining dependence06	-0.210				-0.354**			
	(0.134)				(0.159)			
Oilgas revenue06		0.213				-1.084***		
		(0.321)				(0.270)		
Coalrevenue06			0.173				-1.100	
			(0.813)				(0.858)	
Mining revenue06				0.232				-1.067***
				(0.322)				(0.236)
Earthquake	-0.0370***	-0.0326***	-0.0335***	-0.0321***	-0.035***	-0.036***	-0.036***	-0.037***
	(0.0124)	(0.0117)	(0.0118)	(0.0118)	(0.012)	(0.012)	(0.012)	(0.012)
labforce05	-0.199	-0.187	-0.228	-0.189	-0.194	-0.338*	-0.202	-0.285*
	(0.196)	(0.195)	(0.194)	(0.192)	(0.191)	(0.181)	(0.189)	(0.173)
lgdp_percap05	-0.109***	-0.159***	-0.141***	-0.163***	-0.084*	-0.042	-0.126***	-0.041
	(0.0359)	(0.0350)	(0.0338)	(0.0377)	(0.045)	(0.052)	(0.037)	(0.050)
lpop_05	0.00144	-0.00287	-0.00175	-0.00278	0.014	0.006	-0.005	0.012
	(0.0233)	(0.0240)	(0.0237)	(0.0238)	(0.022)	(0.024)	(0.023)	(0.023)
DURBAN	-0.00742	0.0343	0.0254	0.0373	-0.022	-0.019	0.012	-0.013
	(0.0455)	(0.0412)	(0.0452)	(0.0415)	(0.051)	(0.053)	(0.046)	(0.050)
DJAVA	0.0386	0.0508	0.0436	0.0534	0.024	-0.006	0.035	-0.021
	(0.0406)	(0.0438)	(0.0415)	(0.0447)	(0.040)	(0.040)	(0.040)	(0.040)
Constant	0.973***	1.172***	1.124***	1.185***	0.727***	0.777***	1.102***	0.674**
	(0.284)	(0.303)	(0.278)	(0.308)	(0.280)	(0.272)	(0.264)	(0.267)
Kleibergen F Stat					28.13	21.50	16.29	9.995
Hansen's J, p-val					0.0405	0.164	0.823	0.448
Endog p-val					0.182	0.0844	0.0387	0.0309
Observations	390	390	390	390	390	390	390	390
R-squared	0.093	0.089	0.085	0.090	0.088	-0.067	0.080	-0.076

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Instruments for IV-GMM model use historical resource abundance (in continuous form) and physical resource production in 2006.

Appendix 2.3. First-stage regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Δmindep	ΔIncome	Δoilgasrev	ΔIncome	Δcoalrev	ΔIncome	Δminrevrev	ΔIncome
Earthquake	-0.001	-0.036***	0.001	-0.036***	-0.002**	-0.036***	-0.001	-0.036***
	(0.009)	(0.012)	(0.002)	(0.012)	(0.001)	(0.012)	(0.002)	(0.012)
Δlabforce	0.029	0.064	-0.006	0.059	-0.059***	0.001	-0.066*	0.064
	(0.056)	(0.181)	(0.041)	(0.182)	(0.016)	(0.193)	(0.040)	(0.181)
lgdp_percap05	-0.018	-0.104***	-0.046***	-0.096***	0.010**	-0.128***	-0.033***	-0.104***
	(0.014)	(0.035)	(0.009)	(0.034)	(0.004)	(0.036)	(0.007)	(0.035)
lpop_05	-0.004	0.021	0.001	0.019	-0.007***	0.002	-0.007	0.021
	(0.007)	(0.021)	(0.004)	(0.021)	(0.002)	(0.026)	(0.004)	(0.021)
DURBAN	-0.018	0.027	0.015	0.020	-0.009***	0.028	0.004	0.027
	(0.015)	(0.043)	(0.011)	(0.043)	(0.003)	(0.046)	(0.010)	(0.043)
DJAVA	-0.081***	0.004	0.027***	0.005	-0.003	0.025	0.025***	0.004
	(0.018)	(0.043)	(0.007)	(0.042)	(0.003)	(0.045)	(0.007)	(0.043)
<u>*Instruments:*</u>								
Oilgas abundance	-0.043***	-0.075**	-0.032***	-0.078**			-0.037***	-0.075**
	(0.012)	(0.032)	(0.012)	(0.031)			(0.011)	(0.032)
Coal abundance	0.001	-0.000			0.001***	-0.001	0.001*	-0.000
	(0.001)	(0.001)			(0.000)	(0.001)	(0.000)	(0.001)
ΔOilproduction	0.000***	0.000	0.000***	0.000			0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)
ΔGasproduction	0.000	0.000**	0.000***	0.000*			0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)
ΔCoalproduction	0.000	0.000			0.000***	-0.000	0.000***	0.000
	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.166*	0.575**	0.141**	0.563**	0.061**	0.900***	0.199***	0.575**
	(0.097)	(0.270)	(0.061)	(0.265)	(0.024)	(0.331)	(0.059)	(0.270)
Observations	390	390	390	390	390	390	390	390
R-squared	0.193	0.182	0.412	0.181	0.541	0.083	0.366	0.182

Appendix 2.4. Papers Finding Evidence of a Blessing Effect of the Natural Resources

No	Findings (+)	Authors	Period	Sample	Techniques	Definition of resources
1	Resource abundance (Natural resource capital) is positively correlated with average annual growth in real GDP per capita	Gerelmaa & Kotani (2013)	1990-2010	Cross-country	OLS Regression	The log of the per capita natural resource capital data to estimate the effect of natural resource abundance on economic growth over the period between 1990 and 2010
2	Resource dependence is positively correlated with theaverage annual growth rate of the real GDP per capita	Ouoba (2016)	1980-2010	Panel data, country	Panel data	Resource dependence is the share of total natural resource rents in GDP
4	Resource abundance [total natural capital and subsoil wealth] has a positive effect on economic growth	Brunnschweiler (2008)	1994-2000	Cross-country	OLS and 2SLS,	Log growth of income per cpaita, average 1970-2000 (as dependent variable), resource abundance is defined as the log total natural capital (in US$) per capita, averaged over 1994-2000, and as the log of subsoil wealth (in US$) per capita, averaged 1994-2000 Resource rent is measured as a proxy for natural resource wealth.
7	Oil rent and mineral resources have a positive impact on real income for (Organization of Islamic Cooperation) OIC countries but not for non-OIC countries.	Kunchu, et al. (2016)	1981-2010	OIC (Organization of Islamic Cooperation) countries and non-OIC countries	GMM panel data First-differenced GMM works	Dependent variable uses GDP per capita, oil, mineral natural gas, forestry and coal as the natural resource wealth. All data are obtained from world Bank.
8	Resource abundance has a positive effect on growth	Fan, Fang & Park (2012)	1997-2005	China’s prefectural-level cities,	Linear regression	Resource abundance is measured using the average fraction of mining industry (coal, oil, natural

No	Findings (+)	Authors	Period	Sample	Techniques	Definition of resources
				comprising 206 cities		gas, metal and non-metal ores and other resources) workers compared to the total population. Growth rate is calculated as average rate of GDP per capita of city, from 1997-2005, $G_i = \ln\left(\frac{Y_{2005,i}}{Y_{1997,i}}\right)$
10	Oil and natural gas have a positive effect on economic growth in non-democratic regimes, rather than in democratic regimes	Libman (2013)	2000-2006	Russia, 72 Russian regions	Panel, OLS, Fixed Effect and Two-Way FE	Oil and gas extraction relative to gross regional product (GRP): the extraction value is calclated by multiplying the quantity of oil and gas extracted (in tons and cubic meters, respectively) by the average annual export prices for crude oil and natural gas.
12	Mining has a positive impact on non-mining employment and family income	Fleming, Measham & Paredes (2015)	2001-2011	Australia, 449 non-metropolitan local government areas (LGAs)	OLS	Independent variable is mining employment whics is the (log) change in mining employment in region I between 2001 and 2011. Dependent variable is using two proxies which are non-mining employment growth and income growth model, where median family income is used
13	Coal based employment is negatively correlated with the per cent change in per capita during 1990-2000, when coal prices were low, and positively correlated during 2000-2010, when coal prices were higher.	Betz et al. (2015)	1990-2000, 2000-2010	Continental U.S. counties and specifically within the Appalachian Regional	Cross-section regression	Initial mining industry employment shares consists of coal, oil, and natural gas, and other mining sectors.

No	Findings (+)	Authors	Period	Sample	Techniques	Definition of resources
	A similar effect was found for oil and gas employment.			Commission (ARC)		
15	Boom countries in gas production have higher has positive impact on growth in total employment, wage and salary income and median household income	Weber (2012)	Change between period 1998/99 – 2007/08	209 counties in Colorado, Texas and Wyoming		A Boom county is defined as a county in the top 20% for its upward change in gas production
16	Mining operations and fiscal revenues positively affect social and economic development (as measured by annual growth rate in GDP, direct employment in mining, and in indirect employment,	McMahon & Moreira (2014)	2001-2010	Chile, Ghana, Indonesia, Peru and South Africa (had long mining histories)	Case studies	South Africa and Chile (had a large mining in the 1980's),

Appendix 2.5. Panel data regression (year by year) results using Pooled OLS

VARIABLES	(1) OLS1	(2) OLS2	(3) OLS3	(4) OLS4
Mining Dependence	1.385***			
	(0.0616)			
Mining Revenue		2.529***		
		(0.0873)		
Oil&gas revenue			2.610***	
			(0.0994)	
Coal Revenue				4.604***
				(0.280)
Population (in logs)	-0.159***	-0.123***	-0.143***	-0.129***
	(0.0104)	(0.00994)	(0.0102)	(0.0105)
Labour force participation rate	-0.209**	0.0945	0.215**	-0.386***
	(0.0871)	(0.0871)	(0.0909)	(0.0991)
Household elect.	1.387***	1.332***	1.384***	1.365***
	(0.0449)	(0.0442)	(0.0441)	(0.0477)
Constant	3.875***	3.506***	3.538***	3.890***
	(0.0858)	(0.0862)	(0.0896)	(0.0937)
Observations	4,290	4,290	4,290	4,290
R-squared	0.277	0.347	0.306	0.232

3 CHAPTER THREE

Resource Dependence and the Causes of Local Economic Growth: An Empirical Investigation

3.1 Introduction

There has been a continuing debate about whether resource endowments can help or hinder a country's economy. Traditionally, economic theory assumed that an abundance of natural resources would benefit a country's economy, either as a source to transform economic structures from traditional to industrial, or as a key input of a society's long-term output (Rostow, 1959; North, 1982). Yet after Sachs and Warner's (2001) early investigation found an inverse correlation between resource "abundance" (measured as each country's share of primary exports to total GNP in 1970) and average growth in GDP per capita, other studies began to try to investigate the "resource curse", and the transmission channels through which resources could be hindering growth.

In contrast, in my previous chapter, I found that, other than coal, resource dependence seems on average to have boosted Indonesian district per capita income, implying that resources have been a blessing there rather than a curse. Thus this chapter tries to investigate the mechanisms that resource dependence may be acting through to raise income. Previous papers trying to explain a resource curse have proposed causal mechanisms which could account for adverse resource effects on growth in aggregate income. Some channels proposed have been crowding out of a country's manufacturing (called the "Dutch disease"), demand-side depression of human capital investment or education, downward pressure on institutional quality, and more recently through pervese incentives regarding public spending or public investment (Bhattacharyya and Collier (2014); Collier and Goderis (2009); Karimu et al. (2017)). I will therefore concentrate here on these four prominent candidates.

The theory of the first channel says that a commodity boom in minerals hinders the expansion of a country's tradable sectors as commodity exports cause the local currency to appreciate, making it harder to export manufactured and agricultural products. Consequently, if the manufacturing sector is believed to be a key driver of long-run growth, this mechanism lowers long run growth performance, most notably in subsequent resource bust periods (Sachs and Warner (1997), Stijns (2005)). Secondly, resource dependence also tends to be associated with poor institutions. In general, countries with higher dependence on resources have typically suffered from a high level of corruption within government, low levels of democratisation, and poor implementation of the rule of law, which in turn affect growth (Ross, 2001; Isham et al., 2005). Thirdly, it has been argued in the resource curse literature that human capital accumulation is also commonly hindered by extractive sectors, e.g. coal mining, where there are incentives for young people to discontinue their schooling to get well-paying but low skilled entry level jobs (Gylfason, 2001a; Gylfason and Zoega, 2006; Black, McKinnish, and Sanders, 2005). Finally, some resource curse papers discuss the negative impact of resource windfalls or rents on the composition of government spending, distinct from institutional quality. If resource windfalls are spent unwisely, i.e. for unproductive expenditures such as administrative or personnel spending, this too may slow long-run growth (Aragón, Chuhan-Pole, and Land, 2015).

However, research about whether resource intensity actually works through these transmission channels to negatively or positively affect growth has been far from conclusive. On the one hand, several empirical papers have indeed found a negative effect of resource dependence on school enrolment rates, or on public expenditures on education as a proxy for human capital investment (Gylfason, 2001; Edwards, 2016a). Resource dependence has also been found to delay manufacturing sector expansion ((Sachs and Warner (1995), Stijns (2005)) and to worsen institutional quality by increasing incentives for rent-seeking behaviour, or unaccountable management of revenue windfalls (Ross, 2001; Isham, et al. (2005)).

Yet at the same time, other researchers have found positive effects of resources on growth via these same channels. In the case of the Dutch disease, van der Ploeg (2011) has shown that the phenomenon is less likely to happen in a country that initially has a relatively low share of manufacturing in GDP. Bulte, Damania and Deacon (2005) in an earlier study, also have found cases where resource-rich countries experienced expansions in manufacturing during oil booms. Similarly, with respect to education, Stijns (2005) and Alexeev and Conrad (2011) find higher resource intensity leads to higher education enrolment levels. Again, with respect to institutional quality, Brunnschweiler (2008) and Brunnschweiler and Bulte (2008) find that resource intensity has no effect on measures of rule of law or government effectiveness, and thus no effect on growth through this channel, countering the downward pressure argument.

These conflicting findings regarding causal mechanisms are perhaps not surprising since, as pointed out in the first chapter, there is as yet no consensus among previous studies regarding the overall association between resource intensity and economic growth. Overall resource effect findings may differ because researchers use different resource measures (dependence or abundance)[60], data (within-or cross country, cross-section or panel), or quantitative methods (see for example, van der Ploeg and Poelhekke (2016)). However, a majority argue that negative associations are more likely to occur in developing rather than developed countries (Arezki and van der Ploeg, 2011; Frankel, 2010).

Finally, both resource curse and blessing papers have proposed a variation of the institutional quality causal mechanism. This variation is that it is the exogenous degree of institutional quality (e.g. degree of corruption, accountability, and rule of law) that nations possess that determine whether resource dependence aids or hinders growth. Here, resources are said to aid growth for countries with strong institutions, but hinder it for those with weak institutions (Arezki & van der Ploeg (2010), Papyrakis (2016), Mehlum, Moene and Torvik (2006)). This argument is distinct from one that says rising resource intensity itself lowers institutional quality, thereby slowing growth.

As most empirical studies on the resource curse have used international country datasets, most tests of causal channels have also used such datasets, or tried to investigate causal channels within countries using insights from the cross country literature. In the case of Brazil, Caselli and Michaels (2013) find oil-related revenue increases the supply of teachers and classroom facilities at the municipal level, though the evidence is not robust to alternative specifications. On the contrary, Douglas and Walker (2016) find evidence that the initial dependence of a region on coal mining is positively correlated with the high school dropout level in the Appalachian region of the United States.

Given the prominence of these proposed transmission channels in the resource curse/blessing literature, I will here investigate the extent to which they can explain the apparently positive effect of resource dependence on economic growth within Indonesia. Given the positive overall effect I find for resource dependence, I investigate the following four channels: positive spillovers to manufacturing sector performance, positive effects on

[60] Resource dependence is commonly defined as flows generated from resource extraction activity while resource abundance refers to the known stock of oil or minerals reserves/ deposits in the ground (see Brunnschweiler (2008) for more discussion).

education supply, positive effects on institutional quality, and positive effects on the quality of local government spending. The first three candidates have been identified in previous between-country empirical papers, while the fourth has been identified by more recent empirical papers at the sub-national level in some developing countries (e.g. Brazil, Peru, Sub-Saharan Africa, Colombia, and Indonesia).[61] Note that for resource curse cases, previous studies have asked whether resource dependence lowers these growth-relevant factors, while for my resource blessing case I am asking if resource dependence raises them. I believe that using this approach is beneficial for two reasons. First, this is the first within-country investigation of the mechanisms by which resource dependence affects growth in Indonesia. Second, this investigation can either verify or challenge what recent empirical studies have found regarding causal mechanisms elsewhere.

More generally, this study aims to provide further insight regarding the positive direct effect of resource dependence on district economic growth in Indonesia in its post-decentralisation era. It will ask whether the causal channels chosen here are affected by resource dependence, and in turn whether they affect the rate of economic growth. It will also address the auxiliary question of whether resource dependence is a blessing for districts who have good initial quality institutions, and a curse for those who do not.[62]

This chapter is structured as follows: Section 3.2 provides a literature review of transmission channels between resource dependence and economic growth. Data sources and empirical estimation strategies are explained in Section 3.3, while Section 3.4 provides empirical results and discussion. Section 3.5 concludes.

3.2 Literature Review

3.2.1 Causal Mechanisms of the Resource Curse Hypothesis

Having identified four potential causal channels by which resource dependence can affect growth, I will provide more detail here on each, based on the resource curse/blessing literature.

[61] See for example Caselli and Michaels (2013), Loayza and Rigolino (2016), and Cust and Rusli (2016).

[62] I will use two different measures of district level institutional quality: one of longer duration that captures administrative capacity and one of shorter duration that also captures local government performance indicators.

3.2.1.1 The manufacturing sector and Dutch disease

An early explanation for the resource curse was that a high dependency on natural resources delays or crowds out development of the manufacturing sector, whose development would otherwise generate greater positive effect than the resource sector in raising GDP over time. This hypothesis is called the "Dutch disease" because it was first introduced in the *Economist* magazine after the discovery of natural gas in the province of Groningen in the Netherlands in the late 1950's (Frankel, 2010). As documented by Davis (1995), the resulting rapid expansion of mining and exports from Gronigen led to an appreciation of the Dutch *Gelder*, which in turn decreased the output of the non-resource sectors such as manufacturing and agriculture. This spillover effect was one of the first, and primary causal explanations for the resource curse.[63] I will explain it in greater depth below.

As explained in Figure 3.1, a country's trade (say of resource exports) generates a stream of capital inflows and of resource investment. In a time of resource price booms or resource discovery, a rise in these resource exports can cause a country's currency to appreciate *vis a vis* the rest of the world. This appreciation leads to uncompetitiveness of the country's manufacturing sector as the price of its goods internationally will be higher than that of its competitors in monetary jurisdictions without resource booms. In short, the resource boom causes a stream of capital inflow appreciating the real exchange rate, and reducing exports of the non-resource sector (commonly manufacturing). This short term change in the composition of a country's production and exports can harm its growth over time if the spillover benefits of some sectors (manufacturing) are greater than those of others (resource extraction).

Sachs and Warner's studies (1997, 2001) appeared to provide some support for the Dutch disease hypothesis. Evidence for crowding out has often been taken from the effects of resource development on the performance of exports of manufactured goods. Stijns (2005) for example, using cross-country analysis finds that higher oil and gas reserves are associated with a smaller proportion of manufacturing exports in total exports. Despite this fact, Stijns also finds that having larger coal abundance, comprised of recoverable anthracite, bituminous, lignite and subbituminous reserves, seems to have a positive effect on real growth in the non-resource sector, and a larger share of manufacturing exports in total exports.

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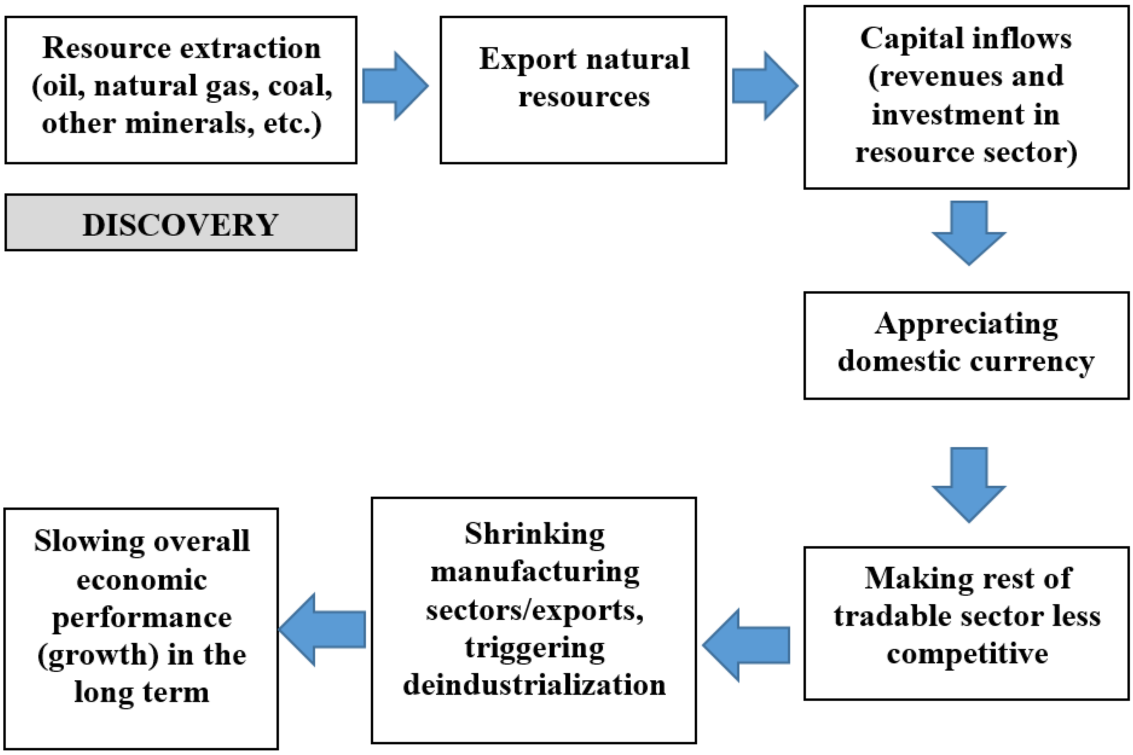
[63] Aragón et al. (2015) argue that Dutch disease can be thought of as deindustrialisation driven by resource windfalls.

Papyrakis and Raveh (2014) in the case of Canada find that mineral production (oil, gas, minerals) is negatively associated with growth in non-mineral exports internationally, while for growth in domestic exports (to other Canadian provinces and territories), the effect of mineral production is not significant.

A more descriptive study from Usui (1997) explores a comparison between Indonesia and Mexico in avoiding the Dutch disease. Using some informative economic indicators, Usui finds that an increased share of petroleum exports in total exports in Indonesia over the period of an oil bonanza in 1970-1975 actually raised the percentage share of the manufacturing sector in GDP, while in the case of Mexico the manufacturing sector's share in total GDP held constant. After the oil boom ended between 1975-1982, as the share of petroleum in exports declined gradually, Indonesia successfully maintained the performance of its manufacturing sector with a substantial rise in its percentage of GDP. According to Usui, Indonesia avoided a Dutch disease effect because it invested its accumulating surplus from oil revenues during the boom period on investments to accelerate growth in non-primary tradable sectors, particularly manufacturing. In a similar way, but looking more recently in the 2000's, Feryawan (2011) conducts a descriptive study that seems to find the opposite of a Dutch disease for Indonesia. Feryawan argues that the mining sector, especially oil and gas extraction, has had positive spillover effects that expanded the manufacturing sector for the country as a whole, though he does not use regression analysis. Empirically, a more recent study by Ito (2017) finds some evidence that a Dutch disease has not occured in the case of Russia, using quarterly time series data from 2003 to 2013 and Vector Error Correction Modelling (VECM). With greater oil abundance than any other country in the world, even in Russia oil-price shocks that caused appreciation of its real exchange rate did not prevent a slight rise in its manufacturing output.

Figure 3.1 The Route of the Dutch Disease Mechanism on Growth



Sala-i-Martin and Subramanian (2013) in their re-investigation of Sachs and Warner's data again do not find a clear significant positive or negative association between countries' degrees of resource dependence and the size of their manufacturing sectors as a share of GDP. Using within-country data, a more recent study by Estrades et al. (2016) find in the case of Uruguay that resource-driven currency appreciation does not significantly affect the output of any sector there, nor does it affect growth of any sector in the long run.

Finally, Aragón, et al. (2015) point out that resource wealth may significantly affect a country's level of industrialisation, but question whether currency appreciation and deindustrialisation will lower growth in GDP over time, rather than merely change its composition. In any event, Aragón et al. conclude that resource booms might not create as much deindustrialisation as some studies predict. Instead, they argue that resource booms may help the development of related types of manufacturing.

3.2.1.2 Human Capital Investment

Researchers in growth and development generally agree that a country's investment in human capital via education is important for long-run economic growth (Barro, 2001).

Education is often measured using years of schooling, school enrolment rates, or proportions with certain levels of attainment.[64] An increase in high school enrolments, for example, can have a positive effect on productivity and growth in income per capita, and vice versa. The positive effect of education on growth has been found in many studies (Barro, 2001; Hanushek and Wöbmann, 2007; Sebastian-Perez and Raveh, 2015).

However, a theory for the resource curse explains that resource abundance may decrease growth performance by reducing the amount of education demanded by local citizens as reflected by low public school enrolment or underfunding. Thus resource dependence can lead to reduced human capital accumulation and slower long term growth. Gylfason (2001) and Gylfason and Zoega (2006) argue, for example, that natural resource dependence may crowd out human capital accumulation on the demand side, lowering the relative return to individuals from acquiring it. This could occur if the resource extraction sector of a resource-rich country provides widespread employment for low skilled workers, thereby reducing the incentive for young people to continue with additional schooling required for employment in non-resource extraction sectors. In short, an expansion of resource-based sectors may create jobs which require less education. This could increase the wage of uneducated workers, narrowing the wage gap with educated workers, and creating incentives for young people to delay or forego additional education as its opportunity cost rises. A decrease in the number of educated people may in the long run reduce growth in output (Walker, 2013; Douglas and Walker, 2016; Gylfason, 2001).

Gylfason (2001) tests this argument using country level data between 1980-1997, and finds a negative correlation between share of natural capital in total capital, and public expenditure on education. Gylfason also shows that having resource wealth can lead to a decline in average years of schooling for girls, and in the level of boys' and girls' enrolment in secondary school. Thus resource endowments might be crowding out human capital accumulation, slowing development over time. Black, McKinnish and Sanders (2005) similarly argue that booms in the oil sector raise the opportunity cost of people going to school as local wages rise, creating incentives for them to leave school. This is thought to be why

[64] In resource curse studies, school enrolment rates are most commonly used as a measure of human capital accumulation (see Davoodi and Zou (1998); Gylfason and Zoega (2006), Carmignani and Chowdury, n.d.) and Sebastian-Perez and Raveh (2015).

the high school drop-out rate in the Appalachian region in the United States increased substantially during the coal boom in the 1970's (Black et al., 2005).

Douglas & Walker (2016) also find support for the education demand channel in more recent empirical analysis of the effects of coal abundance on education in the Appalachian counties of the United States. Douglas and Walker assume that because mining employment does not need high levels of education, or even a high school degree, it potentially reduces human capital accumulation as a source of long run growth. They find that indeed coal mining dependence negatively affects education attainment with the effect on high school completion stronger than that on college completion. Of course, some resource extraction activities require higher levels of skill or education than others, or are less labour intensive. Nonetheless, these studies have confirmed a negative effect of increased resource abundance or dependence on education attainment, with presumed knock on effects on longer term economic performance.

In contrast, a few papers have found contrary evidence regarding resource dependence and human capital investment. For example, Blanco and Grier (2012) find no significant effect of overall resource dependence on either physical or human capital in 17 Latin American economies. In even greater contrast, when decomposing natural resources into specific types, Alexeev and Conrad (2011) find that per capita oil output has a positive and significant effect on primary and secondary school enrolment rates. They also find a positive association between the share of resources in Gross National Income (GNI) and primary school enrolment rates. Similarly, using United States state level panel data, James (2017) finds the enrolment rates in public schools tend to be relatively high in resource-rich states, as do teacher salaries and teacher-student ratios. James also finds a positive association between resource-rich endowments and public spending in education. In the case of provincial level analysis for China, Wul & Lei (2016) similarly find a positive association between human capital accumulation and resource abundance with both positively correlated with sustained growth. These contrary findings could arise because resource dependence does not always depress education demand, or because resource windfalls may offsettingly increase education supply.

3.2.1.3 Institutional Quality

The third causal mechanism commonly proposed between resource dependence and growth is the quality of institutions. The so-called "rentier state" theory predicts that resource wealth makes governments less dependent on taxing their populations, which in turn makes them less accountable to the citizens they govern (Deacon & Rode, 2015; Deacon, 2011). This results in poor quality economic institutions, (or rules by which the economy operates as in North (1991)), thus reducing growth. This argument is often linked with theories of rent-seeking, which claim that resource-abundant countries have experienced a higher incidence of corruption compared with non-resource abundant countries.

Most scholars in the broader growth literature recognize the importance of good institutions for growth (e.g. Acemoglu, et al. 2005) and so it is perhaps not surprising that resource curse scholars have investigated what effects if any resource abundance or dependence has an institutional quality. Resource dependence may provide public officials with greater scope for rent-seeking behaviour, unaccountable bureaucracies, and corruption. Yet resource revenue windfalls could also lead to stronger institutional quality if governments use them to implement better governance practices. Finally, resource dependence may not affect institutional quality *per se*, but might pose a blessing or a curse for growth conditional on the exogenous quality of the institutions a society has.

Thus the link between resources, institutions, and growth can be split into three hypotheses: (a) Natural-resource intensity may affect institutional quality which in turn affects economic outcomes (Isham et al., 2005; Bulte, Damania and Deacon, 2005); (b) Institutional quality is exogenous to resource intensity but determines whether resources spur or hinder growth (Mehlum, et al. 2006); and (c) There is no association between resources and institutional quality (Brunnschweiler, 2008; Alexeev and Conrad, 2011). I will elabourate on the first two options listed above.

The most common form of the first proposition is in the negative form, and says that resource abundance or dependence will have an adverse effect on the quality of institutions. Ross (2001) provides empirical evidence that resource-dependent governments are less dependent on tax revenues from the general population, making them less accountable to their populations. This impact can be more pronounced for point-source resources in particular (see Isham et al. (2005)). For example, Bulte, Damania and Deacon (2005) using cross-country data in 97 countries find that countries that have a high share of fuel and mineral exports have lower rule-of-law indicators and lower measures of government effectiveness. This association is absent for countries with high shares of exports of more broadly based production, such as food and agriculture. Similarly, Busse and Groning (2012) use panel data following 129 countries over the years of 1984-2007, and distinguish their sample between 86 developing and 43 developed countries. They find that an increase in the share of natural resource exports in GDP is negatively associated with institutional quality measures such as the control of corruption. Busse and Groning also indicate that developing countries as a sub-group have a positive association between dependence on resources and degree of corruption.

Ross (2001) and Isham et al. (2005) refer to this detrimental effect of resource intensity on development as "rentier" effects. These effects are most likely to occur in resource abundant countries when revenues can be easily generated by extracting point resources, such as oil, coal, and minerals. Another consequence of rents is that they can enable states to fund repressive regimes which in turn may suppress dissent in ways that increase conflict and lessen incentives for private innovation.[65]

While some studies seem to support this negative flow from resources to institutional quality to lack of growth, other studies fail to find support for this hypothesis. Some studies find no significant effect of mineral resource abundance on institutions, or even suggestive positive effects. Brunnschweiler and Bulte (2008) and Brunnschweiler (2008) in cross country analysis find positive and significant effects of total natural capital and sub-soil wealth assets per capita (averaged 1970-2000) on two governance quality indicators (rule of law and government effectiveness). This positive effect, however, was not robust to the addition of controls for initial income levels. Alexeev and Conrad (2009) similarly fail to find that resource dependence worsens institutions. Using the ratio of mining in GDP, as well as mining output per capita, Alexeev and Conrad find no statistically significant effect from these mining measures on the rule of law index (for the year 2000). Recently, Karimu et al. (2017) find resource rents (as a share of GDP) significantly improve public investment, though the strength of effect depends on institutional quality. Karimu et al. find that if resource windfalls are managed well, they have a positive effect on growth. Similarly, di John (2011) also finds little evidence that resource wealth raises corruption practices, countering the rent-seeking argument. In di John's detailed survey, corruption levels in mineral abundant countries were lower and rose less than in non-mineral countries during the periods of 1965-

[65] Both Sachs and Warner (1995) and Gylfason and Zoega (2006) argue that natural resources may encourage poor insitutional rules by encouraging "rent-seeking" behaviour and a corruption culture. Resources foster close and hidden connections between extraction companies and government, as the latter has the power to issue exploitation licenses. This weakening of accountability for royalties revenues may aggravate government ineffectiveness, creating a poorer investment environment, and slowing economic growth.

1990 and 1990-2000. Di John also critiques the rent-seeking or rentier-state theory for failing to explain counter examples of long-run growth in developing countries such as Bostwana, Malaysia and Venezuela.

As foreshadowed, an alternative hypothesis is that a country's institutional quality is not affected by its resources but that its exogenous institutional quality determines whether resources help or hinder growth. Mehlum et al. (2006) have convicingly claimed that resources slow the growth of a country's economy if it already has poor quality institutions, as reflected by a weak rule of law, a high degree on corruption, or ineffective bureaucracy. Informally, Mehlum et al. classify two types of institutions: "producer-friendly" and "grabber-friendly". Producer-friendly institutions encourage income growth because they build secure business environments and attract entrepreneurs and investment. By contrast, grabber-friendly institutions reward unproductive activities of seeking wealth-transfers, reducing incentives for production.

Mehlum et al. (2006) empirically test this hypothesis by regressing country-level average growth in real GDP per capita from 1965 to 1980 on resource dependence, measured as a share of primary exports in GNP in 1970, along with institutional quality and an interaction term between the two. They find the coefficient of the interaction term is positive, implying that as institutional quality improves, the negative effect of dependence on growth diminishes. This method has subsequently been widely used, for example by Arezki and van der Ploeg (2011), Libman (2013), and by Bhattacharyya and Hodler (2010). Oyinlola, Adeniyi and Raheem (2015) use this approach in the case of Africa using 47 countries and panel data analysis. They too find a positive and significant interaction effect, though their main effect of resource dependence on growth does not confirm Sachs and Warner's original negative finding.

A rare contrary finding regarding Mehlum et al's. hypothesis comes from a cross-country study by Brunnschweiler (2008) using the interaction term approach in an OLS framework. Brunnschweiler tries three alternative measures of resource abundance: total natural capital, mineral resource assets and Sachs and Warner's resource export dependence measure. In contrast to Mehlum et al. when Brunnschweiler uses the first two resource measures, she finds the coefficient on the interaction term is negative, and that the main effect of resource abundance is positive. This implies that resource abundance spurred growth in countries with the poorest institutional quality and that higher institutional quality reduced the growth caused by resource abundance. However, when Brunnschweiler used the last measure of resource dependence, the results were consistent with those of Mehlum, et al. (2006). Based on her main findings, Brunnschweiler concludes that: *".... the more institutionally and economically developed countries have on average experienced lower positive growth effects of resource wealth*." (page 407).[66]

Bjorvatn, Farzanegan and Schneider (2012) use panel data for 30 oil-rich countries between 1993 and 2005. Bjorvatn et al. stress the effect of resource rents (the share of oil revenues in total government budget) on GDP per capita, but also use the effect of a political fractionalisation index and interact this measure with resource rents. This fractionalisation index is increasing in the number of political parties, which they interpret as a proxy for weak government (similar to Mehlum et al. and Brunnschweiler's exception). Bjorvatn et al. find that oil revenues boost growth, while the interaction term with fractionalisation is negative and significant, implying that weak government diminishes the positive effect of oil rents on growth.

3.2.1.4 Composition of Public Spending from Revenue Windfalls

The last causal theory is associated with a proposition following the classical theory of fiscal federalism (Tiebout, 1956). This theory assumes that local governments are better informed about local preferences than national governments, and can thus provide better quality public spending as needed by local populations. Under such optimistic conditions, if resource revenues exist and are transferred to local governments, as some countries have done under fiscal decentralisation, this may improve accountability and public service delivery. Better public spending could in turn spur economic growth.[67]

[66] Alternatively, Arezki and van der Ploeg (2010) using cross country analysis covering the period 1965 to 1990 do not find any statistically significant evidence of institutions or interaction between institutions and resource dependence on growth, either employing OLS or IV estimation.

[67] With regard to whether public investments have positive significant impacts on growth, some empirical studies still find mixed results. A study from Davoodi and Zou (1998) using cross-country regression, on the other hand, finds a weak negative relationship, between public spending and economic growth. Atkinson and Hamilton (2003) argue that positive and negative findings could arise depending on the extent to which investments (as a share of government investment in GDP) are allocated to productive uses. In their study, Atkinson and Hamilton regress government expenditure allocation on economic growth using cross-country regression in countries from Central America, the Middle East and North Africa, the OECD, and Sub-Saharan Africa in the period 1980-1995. They find negative signs on both government investment and consumption on growth, but both are insignificant.

Among resource curse scholars, Atkinson and Hamilton (2003) are the first scholars who identify whether resource dependence could affect growth through its effects on the composition of public expenditures. They argue that resource wealth may hinder growth when governments poorly invest windfall resource revenues. Cust and Poelhekke (2015) express similar views specifically when under fiscal decentralisation policy resource royalties flow to local governments. In contrast to Tiebout's optimism, Cust and Poelheke argue that such royalties may lessen growth if local level governments lack the capacity to administer resource windfalls. Others argue that a resource curse arises only where a country's government (of whatever level) is unable to manage its resource revenues (Atkinson and Hamilton, 2003). Similarly, Collier & Goderis (2009) argue that government use of revenues generated from resource extraction may be inefficient, as governments face less pressure to account for its use than revenues raised via more broadly based taxation. Resource wealth can thus bring positive or negative effects on economic welfare, depending on the composition of government spending between genuine investments vs. wasteful consumption (Aragón, Chuhan-Pole and Land, 2015; Aragón and Rud, 2013).

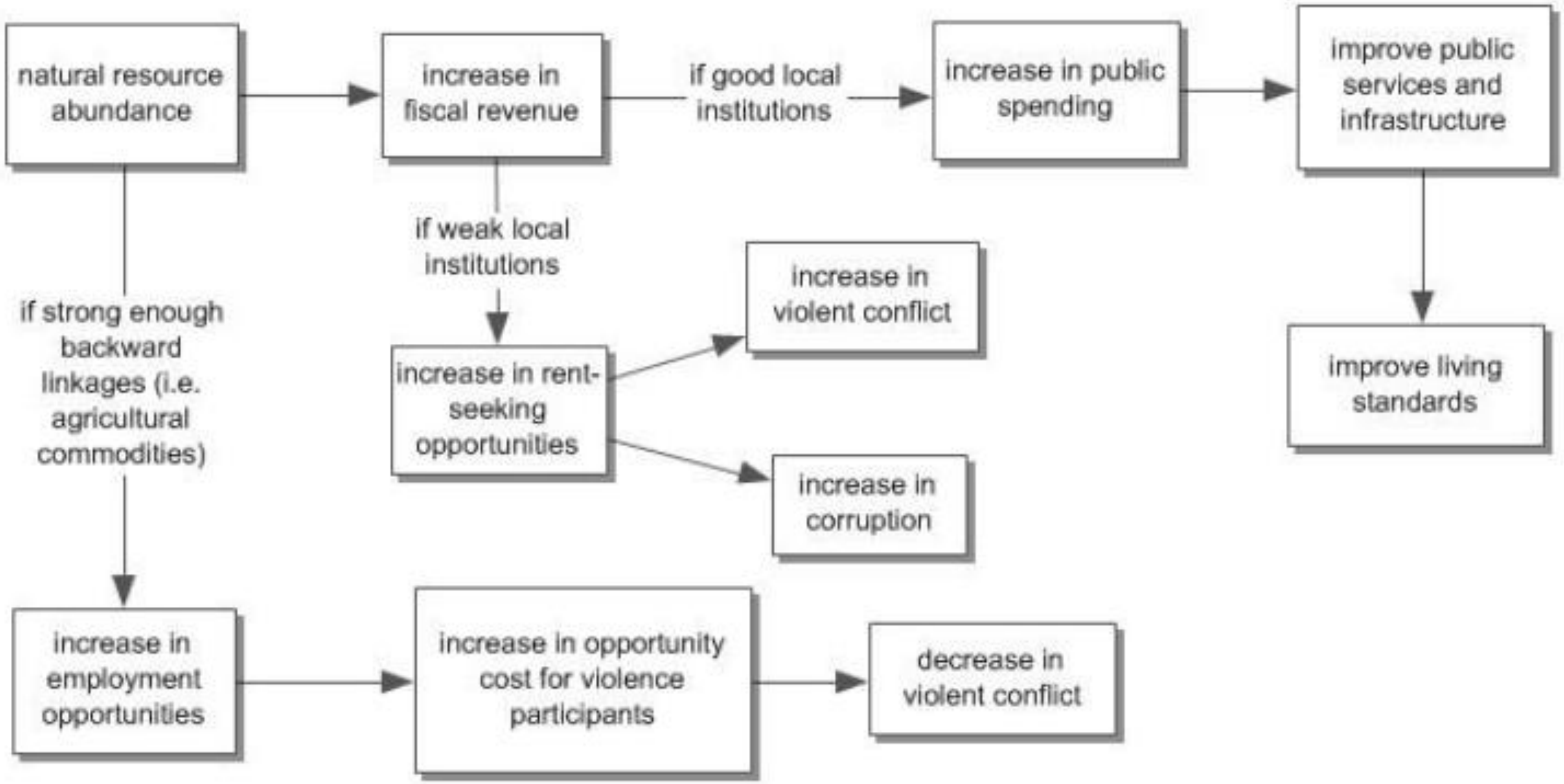
In theory, Aragón, et al. (2015) identify both positive and negative potential effects of revenue windfalls on government spending in resource-rich emerging economies. As Aragón et al. illustrate in Figure 3.2, revenue windfalls can expand public spending as a consequence of higher budget constraints. With strong institutions and effective governance, these resource revenue streams will be invested for local public provision such as public infrastructure, health care and education quantity or quality. These capital expenditures create spillover effects on the overall economy, raising incomes and living standards. On the other hand, revenue windfalls may hamper growth if they incite conflict within society generated from unfair distribution. Such conflicts may be more likely when institutions are weak, or government is ineffective in redistributing resource windfalls.

Bhattacharyya and Collier (2014) using data from the OECD and developing countries between 1970 and 2007 find that resource rents lower the level of public capital stock. They stress that for resources to boost growth, investments in resource-abundant countries should focus on public capital such as education, health and infrastructure.[68] Likewise, using provincial data from China, Zhan, Duan and Zeng (2015) also find that resource dependence

[68] In their empirical paper, Bhattacharyya and Collier (2014) find increased resource rents have been associated with lower public investment, though they attribute this to poor institutional quality.

lowers government spending particularly on human capital-enhancing public goods such as education and health care. On the other hand, some papers show positive effects of resource revenues on the size or composition of public spending. Karimu et al. (2017), for example, focusing on resource-rents in 39 Sub-saharan Africa countries between the period 1990-2013, find that total natural resource rents are positively associated with government investment. Total rents here are defined as the sum of rents from petroleum activities, natural gas production, coal, minerals, and forest resources, while government investments include the level of public capital spending both at the central and regional level. Karimu et al. find that the increase in spending increases economic growth. Likewise, in a within-country study of Brazil, Caselli and Michaels (2013) find that municipal oil revenues increase spending in public investment, such as housing and urban development, transportation and education.

Figure 3.2. Revenue Windfall Effect and Transmission Channels



Source: Aragón, et al. (2015, p.49)

3.3 Data and Estimation Strategy

3.3.1 Data

To investigate whether the resource blessing for Indonesia has worked through my four candidate channels I use the same data as in my first chapter, including the time period from 2006-2015. However, as the main purpose of this chapter is to test some potential causal channels of resources on growth in per capita income, several new data series are used.

All additional data come from various Indonesian government ministries, which I then combine with the Indonesian Statistical Agency (BPS) dataset. For education, I use the district level high school enrolment rate from the Ministry of Education and Culture. Data on capital vs. non-capital spending comes from the Ministry of Finance. According to the BPS definition, capital spending comprises all expenses paid to produce tangible fixed assets whose benefit or value continues more than a year. It ranges from, for example, public servants' office equipment, such as computers or photocopy machines, to road constructions, bridges, public buildings, etc.

Measuring the quality of institutions at district level in Indonesia presents some challenges, as the Indonesian central government does not have a single standard measure covering all years of my analysis. Administratively, the central government did not have an instrument to evaluate district institution quality when decentralisation began in 1999 or when its implementation was completed in 2004. Fortunately, the Indonesia Audit Board (or BPK) did begin to issue audit reports which scored each district beginning in 2006. This audit score only captures each district's ability to manage and produce financial statements to an approriate government accounting standard. Each district receives an assessment result based on auditor opinion after inspection, and is scored on a scale from 1 to 4, with the score increasing in assessed compliance.[69] In spirit, this audit score captures the level of local administrative capacity, rather than the level of local corruption, though it may serve as an indirect proxy for the latter.

A second, more comprehensive measure of institutional quality at district level becomes available in 2010. In 2008, the Indonesian government recognized the need in

[69] The opinion ranges from the worst to the best: cannot give any opinion, here scored as 1, to some degree acceptable = 2; performed well/qualified, but corrections needed = 3; qualified without any exception = 4. These audit reports have been accessible to the public since 2006. This is available in PDF format at http://bpk.go.id/ihps.

Government Rule No. 6/2008 to evaluate district governance more comprehensively. This culminated in a governance composite score that ranges from 0 to 4, with the number increasing in quality of governance. This index contains sub-indicators as follows: (a) compliance with the rules and procedures laid out for local districts in national law; (b) intensity and effectiveness of public consultation processes with local residents; (c) transparency in budget planning, and in reporting sources of income and its allocation; (d) local government innovation to improve the local region.[70] Since 2010, the Ministry of Home Affairs has announced evaluation of each district government's performance index score each year.[71]

Note that even my first institutional quality measure does not enable me to exactly replicate the full years of analysis used in Chapter I. The measure requires the loss of 2006 (now used as a base year).

3.3.2 Empirical Estimation Strategy

3.3.2.1 Causal Channel Investigation

To investigate whether the resource blessing found for Indonesia has operated through any of my four candidate causal channels, I will use a three step procedure. The first step simply repeats the first difference equations estimated in Chapter 2, which provides an estimate of the overall (reduced form) effect of rises in resource dependence on growth in GRDP, now between 2007 and 2015.[72]

My approach for the second step is fairly straight forward. Again using first differences I estimate the extent to which each potential causal channel is affected by resource dependence, as follows:

$$\Delta C_i = \gamma + \beta \Delta RD_i + \sigma \Delta X'_i + \varepsilon_i \qquad \text{.........................} \qquad (1)$$

[70] The guidance on how to explicitly measure this index is explained in the Minister of Home Affairs Rule No. 73/2009.
[71] A decision list of these evaluation scores is published yearly in PDF format on the Ministry of Home Affairs website (http://otda.kemendagri.go.id/).
[72] I use the following regression function: Change in GRDP per capita = f(Change in resource dependence, other control variables), to see the direct effect of resources on district GRDP per capita growth. Both OLS and Instrumental Variable techniques are applied, to account for the possible endogeneity of resource dependence.

The subscript i represents each district, and first differencing is a way to control for the unobserved individual effects of districts. ΔC_i stands for the change in each potential channel. It consists respectively of a change in GRDP from manufacturing ($\Delta Manuf_i$), not in logs, to capture the original size of this sector, a change in high school enrolment rates ($\Delta School_i$), in institutional quality (ΔIns_i), and in public spending ($\Delta Spend_i$). Each is regressed separately, or :

$$\Delta Manuf_i = \gamma + \beta \Delta RD_i + \sigma \Delta X'_i + \varepsilon_i \qquad \text{.........................} \qquad (2)$$

$$\Delta School_i = \gamma + \beta \Delta RD_i + \sigma \Delta X'_i + \varepsilon_i \qquad \text{.........................} \qquad (3)$$

$$\Delta Ins_i = \gamma + \beta \Delta RD_i + \sigma \Delta X'_i + \varepsilon_i \qquad \text{.........................} \qquad (4)$$

$$\Delta Spend_i = \gamma + \beta \Delta RD_i + \sigma \Delta X'_i + \varepsilon_i \qquad \text{.........................} \qquad (5)$$

In each case, ΔRD_i measures the change in resource dependence in district *i* between 2007-2015. As in Chapter 1, I try four alternative measures of dependence, namely mining's share of district GRDP, or the share of district government total revenues that come from mining in general, or from oil and gas in particular, or from coal in particular. I expect that the coefficient on ΔRD_i in equations (2)-(5) will be positive, assuming each channel positively contributes to growth, and given that resource dependence was found to have a positive overall effect on growth. The $\Delta X'_i$ includes a set of control variables that is commonly used in the growth literature, such as changes in the labour force participation rate, the initial level of district population in 2006 (in logs) and the log of GRDP per capita in 2006.[73] Initial population is included to control for potential pro-growth effects of economies of scale. I also control for the total number of earthquake events over the 9 year period. Dummy variables are also included to distinguish urban from non-urban districts (DURBAN) and districts located on Java Island or not (DJAVA), to allow for variation in growth within Indonesia.[74]

The ordinal nature of my institutional quality measures requires some care when put in first differenced form. I begin by treating the auditor scores as cardinal, and take simple difference in each district's score over time. I then reanalyse equation (4) recognizing that the

[73] Some control variables common in the cross-country growth literature are absent. For example, it is impossible to get data on openness to trade at district level.

[74] I do not use the Seemingly Unrelated Regression (SUR) model to estimate (2) – (5) simultaneously because the same control variables, $\Delta X'_i$, are included in every equation. These variables are specified in the step three equation (see below) alongside the main variable of interest, ΔRD_i.

auditor scores are ordinal, and collapsing changes over time to the three possible categories "improved", "stayed same" or "worsened". I then use an ordered probit of (4) (with or without instrumental variables) using the IV-Probit under Conditional Mixed Process (CMP) module in Stata provided by Roodman (2009).

As in my first chapter, I address the possible endogeneity of each district's level of resource dependence over the two years considered by using two types of instrumental variables. I again use as one instrument district resource abundance (RA) measures in the 1970's for oil and gas and coal at district level, which were constructed using historical resource maps mapped to modern district boundaries using ArcGIS Software. Areas containing oil and natural gas deposits had been largely identified by this time. While Indonesia's national government had limited fiscal and technological capacity for exploration prior to the 1980's, it had entered into potential production-sharing agreements with multinational companies who had done so. I also use the second instrument of the difference in physical oil, natural gas, and coal mining production from 2006-2015, following Caselli and Michaels (2013) for Brazil, and Cust and Rusli (2016) for Indonesia.

After testing whether resource dependence affects each potential causal channel of growth, I run the third and final step by regressing the change in real GRDP per capita on ΔRD_i as in step one, but now along with all potential causal channels simultaneously, as well as the other control variables from step one. The step three model is thus :

$$\Delta LnGRDP_i = \gamma + \delta_1 \Delta RD_i + \delta_2 \Delta Spend_i + \delta_3 \Delta INS_i + \delta_4 \Delta School_i + \delta_5 \Delta Manuf_i + \Delta X'_i \, \beta_2 + \varepsilon_i \quad (6)$$

As before, $\Delta LnGRDP_i$ is $Ln\left(GRDP_{i,2015}\right) - ln\left(GRDP_{i,2007}\right)$, capturing growth in per capita income over an eight year period.

Together, these three steps should enable us to test the extent to which the resource blessing experienced by Indonesia is operating via any of the four potential causal channels. The coefficient on ΔRD_i in step one indicates the total reduced form effect of resource dependence on growth. The coefficients on ΔRD_i in equations (2) to (5) of step 2 indicate the extent to which resource dependence is affecting these potential causal channels. Finally, the coefficient on ΔRD_i in step three should indicate the residual effect of resource dependence on growth that is not explained by the four channels. In addition, the coefficients on each of the four channels in step 3 should indicate the extent to which each channel affects growth, whether movements in those channels are caused by resource dependence, or by other influences.

This three step strategy will use ordinary least squares (OLS) and instrumental variables with the feasible efficient two-step GMM estimator (or IV-GMM hereafter) developed by Schaffer, Baum and Stillman (2003).

3.3.2.2 Testing the Effect of Institutions on Whether Resources Help or Hinder Growth

For institutional quality in particular, the three step procedure described above will be used to test the hypothesis that resource dependence itself changes institutional quality, which in turn affects growth. However, many papers have tested the alternative hypothesis that institutional quality is not itself affected by resource dependence, but rather, is critical in determining whether resource dependence will help or hinder growth.

Here I use two methods to test this alternative hypothesis. First, I use an initial baseline level of district institutional quality as a benchmark to rank and separate the districts between the 50% with highest and lowest measured quality. I use the initial financial audit score of each district in 2006, to divide them into two groups of 390/2 = 195 each, and then test if resource dependence subsequently raised growth for the stronger district sample, and lowered growth for the weaker district sample.

I repeat this exercise for my better but shorter duration quality measure using the baseline year 2010. Either way, I then run the same model as in the first step for the stronger and weaker samples separately.

The stronger institutions group specification is expressed as follows:

$$\Delta LnGRDP_{i,stronger} = \gamma + \beta_1 \Delta RD_{i,stronger} + \beta_2 \Delta X'_{i,stronger} + \varepsilon_i \qquad (7)$$

The second group equation is:

$$\Delta LnGRDP_{i,weaker} = \gamma + \beta_1 \Delta RD_{i,weaker} + \beta_2 \Delta X'_{i,weaker} + \varepsilon_i \qquad (8)$$

I also try this with instruments for resource dependence as before, so that the first and second stage regressions are modelled as:

$$\Delta RD_i = \gamma + \gamma RA_{1970s} + \gamma \Delta OIL_i + \gamma \Delta GAS_i + \gamma \Delta COAL_i + \beta_2 \Delta X'_i + \varepsilon_i \qquad (9)$$

$$\Delta LnGRDP_i = \pi_0 + \pi_1 \Delta \widehat{RD}_i + \pi_2 \Delta X'_i + \varepsilon_i \qquad (10)$$

The second method for testing this alternative hypothesis follows Mehlum et al. (2006) in using an interaction term with the whole sample of districts. Here I check whether the beneficial effect of resources on growth is increasing in institutional quality. To implement this, I run a first step regression of the whole sample as before that now includes a measure of institutional quality, and an interaction term between dependence and institutional quality. This takes the form:

$$\Delta LnGRDP_i = \gamma + \delta_1 \Delta RD_i + \delta_2 Ins_{base\ year} + \delta_3 (\Delta RD_i * Ins_{base\ year}) + \delta_4 \Delta X'_i + \varepsilon_i \qquad (11)$$

Here $Ins_{base\ year}$ is institutional quality at a base year of 2006. As before, I also try an instrumental variable approach to account for the possible endogeneity of ΔRD_i including its interaction with $Ins_{base\ year}$. Note that, owing to a lack of Ins measures in 2005, (7)-(11) are run for the difference in values between 2007 and 2015, rather than 2006 and 2015.

3.4 Empirical Results and Discussion

Summary statistics for my potential causal channels and other variables are reported in Table 3.1 in difference form, just as they will be used in regressions. My first-difference models here use 390 observations following the number of districts in Indonesia between 2007-2015.

The average change in real GRDP per capita (in logs) is 0.372 and the standard deviation is 0.340. Note that district changes in resource dependence over this time were small on average, but with large individual cases of both positive and negative change. For example, the largest rise in mining dependence is 0.793 over these eight years. Similarly, the share of local government revenues from resources all rose by as much as 0.239, 0.256, and 0.3660 for oil/gas, mining, and coal, respectively, for individual districts. On average, Indonesian districts became slightly more resource dependent over this time as measured by share of GRDP or local government coal revenues, but local district governments become slightly less dependent on revenues from oil and gas, and thus from mining revenues overall.

Table 3.1. Descriptive Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Δ Real GRDP per capita (in logs)	390	0.373	0.340	-0.876	2.603
ΔMining Dependence	390	0.012	0.139	-0.613	0.793
ΔMining Revenue	390	-0.012	0.085	-0.507	0.257
ΔOilGas Revenue	390	-0.027	0.088	-0.619	0.240
ΔCoal Revenue	390	0.015	0.046	-0.060	0.366
Earthquake	390	0.464	0.936	0.000	7.000
ΔLabour force participation rate	390	0.067	0.114	-0.133	0.415
GRDP per capita, 2006 (in logs)	390	3.958	0.697	1.961	7.609
Population, 2006 (in logs)	390	5.834	1.016	2.534	8.324
DURBAN	390	0.208	0.406	0.000	1.000
DJAVA	390	0.303	0.460	0.000	1.000
Oil and gas deposit_continuous	390	0.154	0.660	0.000	7.000
Coal deposit_continous	390	3.660	14.327	0.000	94.214
OilGas_binary	390	0.059	0.236	0.000	1.000
Coal deposit_binary	390	0.067	0.250	0.000	1.000
Δoil production (thousand barrels)	390	-165.588	3304.062	-22034.380	51931.340
Δgas production (MMBTU)	390	2767.066	33453.220	-336333.700	382843.900
Δ coal production (IDR)	390	61.194	483.250	-3692.962	5614.593
ΔShare spending on capital	390	0.001	0.099	-0.307	0.452
ΔInstitutional Quality (capacity)	390	1.167	1.054	-2.000	3.000
ΔNet enrolment ratio	390	0.163	0.119	-0.172	0.617
ΔManufact (in 10,000 IDR)	390	0.046	0.159	-0.654	1.926
InsQual06 (performance)	390	2.510	0.845	1.000	4.000
InsQual10 (performance)	383	2.468	0.423	0.686	3.240

Note: Detailed definition and variable source are given in Appendix 3.1

Focusing on the four candidate transmission channels, the high school student enrolment rate grew substantially by 16.29 percentage points on average over this eight year period. The share of local government spending on capital fell slightly on average over this time, but with considerable variation across districts. The Institutional Quality (capacity) measure provided by auditors rose sharply on average, though again with considerable variation. Note that with score levels from 1 to 4, differences ranged in practice from +3 to -2. The formal results of testing the association between resource dependence and these four causal channels and how these channels affect district economic performance will be discussed in the next section.

3.4.1 Channels Investigation

As mentioned in section 3.3.2., this investigation follows a three step procedure. I first report the first difference (FD hereafter) results as I did in Chapter 2, showing the overall impact of changes in resource dependence on district growth. Since the data used in this causal channels investigation uses the difference between 2007 and 2015 rather than 2006 and 2015, the results differ slightly from those in Tables 2.7 and 2.8 in the previous chapter.[75]

Table 3.2 presents the overall effect of changes in four different resource dependence measures (ΔMining Dependence, ΔMining Revenue, ΔOilGas Revenue, ΔCoal Revenue). For comparison, I place the results for both OLS regressions and instrumental variable (IV-GMM) estimators side by side. In general, my instruments under IV-GMM seem to have less weakness than with the slightly longer time interval of Chapter 1, ranging from 9.046 for column (2′) to 12.266 and 16.081 for columns (1′) and (3′).[76] Since I have two instruments (historical resource abundance (in continuous form) and change in physical output of natural resources) but only one suspected endogenous variable, I can also report an overidentification test. The Hansen *J* statistics, which are valid in the presence of heteroskedasticity, show that in all models (1′)-(4′), the p-values fail to reject the null hypothesis of exogenous instruments. Hausman-type tests regarding whether the resource dependence measure is exogenous reject this null in models (2′)-(4′) at the 5% level, and are near borderline in model (1’), suggesting as in Chapter 1 that my resource dependence measures are endogenous.[77]

Moving to the results, as I found in the first chapter, in general resource dependence positively contributes to income per capita in local regions. Concentrating on column (3’) of two-step GMM, I find that income per capita growth is significantly raised by an increase in local government dependence on oil and gas revenues. A standard deviation increase in the change in oil and gas dependence is associated with a (=0.0883 * 1.119 = 0.098) 9.8 per cent increase in income per capita between 2007 and 2015. As in Chapter 1, the baseline year

[75] In Chapter 2 I use a 9 year difference, 2015-2006, and retain 2005 as my baseline year. Reassuringly, the results are similar in terms of coeffcient signs and significance. Table 2.7 in the previous chapter used historical resource abundance in continuous form, which is the form I use in this chapter.

[76] An F statistic equal or greater than 10 is commonly acceptable as a benchmark to evaluate instrument strength (Wooldridge, 2016).

[77] For brevity, I report only the coefficients on the key resource dependence variable, though all control variables used in step 1 are also included. Full results are reported in Appendices B through K. Table 3.2 only reports results using the historical resource abundance instrument in continuous form. The results using a binary form are shown in Appendix (B).

GRDP per capita also influences subsequent growth in all models, supporting the convergence hypothesis as postulated in the growth literature.

I turn next to the second step procedure to test whether each potential causal channel is affected by resource dependence. Table 3.3 summarises results using FD under both OLS and IV-GMM, along with test results of instrument weakness, exogeneity, and endogeneity of the main resource dependence variable. Results for each candidate are given in regressions (1)-(4), where each case provides results for my four alternative resource dependence measures. Each candidate is presented in turn, beginning with changes in manufacturing output.[78]

Before interpreting the results, I begin with validity checks for my two instruments for resource dependence. Beginning with regressions for manufacturing and net enrolment ratio, the Kleibergen F statistic shows in general correlations between instruments and resource dependence for manufacturing, with values above 10, or nearly 10, as suggested by Wooldridge (2016, p.478). The same strength also applies for net enrolment ratio, with 3 of 4 values of its Kleibergen F statistic greater than 10. In tests of overidentification, the p values of Hansen *J* tests fail to reject that instruments are uncorrelated with the error term for both manufacturing and net enrolment ratios. Finally, for both causal candidates tests for endogeneity of resource dependence fail to reject exogeneity in IV-GMM models (2')-(4'), but reject it at the 10% level for model (1') (p-value of 0.0397 for manufacturing and 0.0529 for net enrolment variable). Instrument validity test results are similar for regressions regarding public capital spending, with most of the weakness F test values high and the overidentification tests failing to reject the null of instrument exogeneity. Similarly, for public spending exogeneity of resource dependence is rejected only for the first measure of resource dependence, mining's share in GRDP.

Instrument validity results differ, however, for institutional quality regressions. Although the instruments remain strongly correlated with resource dependence measures, Hansen *J* p values are smaller, between the .06 and .10 levels in all models (1')-(4'). This suggests the instruments may be correlated with the structural error terms in institutional quality regressions, and thus not exogenous. However, if we use the stricter significance level of 5%, all models fail to reject instrument exogeneity. Regarding the test of whether resource

[78] Note that for brevity, I only show the coefficients related with the effect of my four resource dependence proxies on each four causal channels transmission. The full results including all control variables are presented in Appendix (C).

dependence is exogeneous using these instruments, only column (2') has a p-value less than 10%, implying that for resource dependence models (1), (3) and (4) OLS results may be valid.

Moving to the findings, in general, rising natural resource dependence increased most of the channels investigated, with the exception of public spending on capital, both in OLS and IV-GMM regression. Beginning with the effects of the four resource dependence measures on manufacturing activity, I find that rises in three of four of them are positively correlated with the size of increases in manufacturing output (measured as real district GRDP in Indonesia currency (10,000 IDR)), with the notable exception of coal revenue dependence. For example, referring to the coefficient in column (2), a standard deviation increase (0.085) in the change in the share of mining revenues in total local government revenues is associated with an increase of (0.085*0.183 = 0.0155) 1.55 percentage points in manufacturing output.

Regarding high school enrolment, in all four OLS estimations, the sign of the effect of rising resource dependence on change in net enrolment ratio is positive, and in 3 of 4 cases statistically significant at the 1 per cent level. These positive associations occur whether dependence is measured through mining's share of district GRDP, or its total share in government revenues, or share of oil/gas revenues, leaving only coal revenue share with no significant association. Focusing on the IV result given in column (1′) as indicated by endogeneity tests, a standard deviation increase in the change in the share of mining dependence raises the enrolment rate of students in high school by (0.139 * 0.381 = 0.0525) 5.25 percentage points.

With regards to public spending composition effects, I find less evidence that rising resource dependence leads to greater proportional spending on capital. Only the OLS estimation for coal revenue dependence has a significant positive impact on local capital spending. For the other three measures of resource dependence and for all IV-GMM models, there is no significant association with proportion of local spending on capital. Taking the only significant result in column (4), a one standard deviation increase in the change in coal's share of total government budget, on average, increases the share of local government spending on capital by (=0.046 * 0.453 = 0.0208) 2.08 percentage points, holding all other factors constant.

Less valid instruments notwithstanding, I also find that all resource dependence measures are positively correlated with institutional quality, contrary to the rent-seeking hypothesis that high dependency on natural resources will make governments unaccountable and unproductive, inhibiting improvements in institutions. Focusing on OLS models, rising resource dependence has a positive significant effect on raising quality of institutions, with the exception being local government dependence on oil and gas revenues, where the positive coefficient is not significant. Interestingly, rising dependence on coal mining revenues seems to have a strong impact on raising district financial administrative capacity, with or without instruments. Taking the example of column (2), a one unit (i.e. 0.01) increase in mining's share of district total budget is associated with an increase in auditor score of 0.0158 index units, while under IV-GMM estimation it is associated with an increase of 0.0321 index units. To summarise, I have so far found evidence that resource dependence is positively associated with three of my four candidate measures: size of manufacturing sector, high school enrolment rates, and institutional quality.

Before proceeding to my third step, however, I relax my assumption treating institutional quality as a cardinal variable. I use instead ordered probit estimation (for audited quality that has risen, stayed the same, or fallen), while the independent variables remain as before. Table 3.4 presents estimated coefficients under ordered probit with and without instruments. I find again that for all resource dependence measures rising resource dependence appears positively associated with changes in institutional quality. However, I now find that in only 2 rather than 3 out of 4 cases, columns (2) and (4), is the association significant at the 5 per cent level. The marginal effects for illustrating the magnitude of effect for each resource dependence measure are reported in Table 3.5. As presented, an increase in the share of local government revenues from mining in its total budget from 0% to 100% increases the probability of institutional quality improving over time by 59.5 per cent and decreases the probability of it worsening by 9.3 per cent. Similarly, an increase in coal revenue dependence tends to increase the probability that institutions improve (the marginal effect of a rise from 0% to 100% is to raise the likelihood of improving by 181 per cent, and to reduce the likelihood of worsening by 28.1 per cent).

As mentioned in section 3.3.2.2, I also show the results of ordered probit using instrumental variables (hereafter IV Oprobit) to deal with possible endogeneity of the main regressor in Table 3.4. The key first stage results of all instruments are shown in each column where IV estimation is labelled. They show that my instruments are indeed significantly correlated with each resource dependence measure at the 1 per cent level, which means that the excluded instruments are not weak. However, the CMP Stata module that I used to perform IV Oprobit does not provide overidentification tests. Therefore, in this regard, I assume that my instruments do not directly affect changes in institutional quality except through their effects on resource dependence. The endogeneity tests of resource dependence are shown by the *atanhrho* p-values. The null hypothesis for this is that each measure of resource dependence is exogenous. Since the results show that all models fail to reject the null, it would suggest that the regular ordered probit estimates may be valid.

For completeness, however, the IV Oprobit models again find a positive association between resource dependence and institutional quality, but again significantly so only in one of four cases: coal revenue dependence. For coal in particular, my OLS or IV Oprobit results may indicate that the coal boom experienced during 2000-2012 has contributed to increasing district government administrative capacity. This could occur if increased coal revenues have been used to raise the quality and training of regional civil servants that might in turn improve administrative processes.

Thus my step two results so far provide evidence that district resource dependence, with the absence of coal dependence measure, has had a positive influence on three factors generally thought to contribute to the change in per capita income: size of manufacturing, high school enrolment rates, and possibly institutional quality. However, I have not yet established whether these three factors, or composition of public spending on capital, actually contribute to income growth within Indonesia, nor the extent to which they can account for resource dependence's overall positive effects on growth. I next move to do this.

Table 3.2. OLS and IV regressions

Independent Variables	(1) OLS	(1′) GMM	(2) OLS	(2′) GMM	(3) OLS	(3′) GMM	(4) OLS	(4′) GMM
ΔMining Dependence	0.678***	1.539***						
	(0.191)	(0.483)						
ΔMining Revenue			0.211	1.032***				
			(0.272)	(0.381)				
ΔOilGas Revenue					0.0385	1.119**		
					(0.384)	(0.494)		
ΔCoal Revenue							0.672	-0.642
							(0.583)	(0.699)
Earthquake	-0.028**	-0.025	-0.029**	-0.0219**	-0.030**	-0.0276**	-0.027**	-0.032***
	(0.013)	(0.019)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)
ΔLabour force partic.rate	0.226	0.237	0.261	0.379**	0.232	0.322*	0.262	0.196
	(0.174)	(0.174)	(0.171)	(0.155)	(0.166)	(0.176)	(0.187)	(0.182)
GRDP per capita, 2006 (in logs)	-0.116***	-0.099***	-0.131***	-0.104***	-0.136***	-0.076	-0.156***	-0.121***
	(0.031)	(0.037)	(0.030)	(0.034)	(0.034)	(0.047)	(0.033)	(0.037)
Population, 2006 (in logs)	0.011	0.022	0.008	0.025	0.005	0.026	0.008	0.002
	(0.022)	(0.019)	(0.024)	(0.019)	(0.024)	(0.021)	(0.024)	(0.024)
DURBAN	0.049	0.073*	0.041	0.045	0.040	0.026	0.058	0.026
	(0.043)	(0.043)	(0.044)	(0.043)	(0.043)	(0.050)	(0.044)	(0.046)
DJAVA	0.083*	0.140**	0.028	-0.009	0.032	-0.025	0.042	0.027
	(0.047)	(0.064)	(0.042)	(0.039)	(0.043)	(0.043)	(0.042)	(0.042)
Constant	0.723***	0.551***	0.826***	0.628***	0.860***	0.542***	0.904***	0.837***
	(0.138)	(0.175)	(0.151)	(0.140)	(0.166)	(0.168)	(0.160)	(0.162)
Kleibergen-Paap rk F stat		12.266		9.046		16.081		14.164
Hansen *J* Stat, p-value		0.4228		0.1824		0.2910		0.9786
Endog test, p-value		0.1195		0.0597		0.0491		0.0079
Observations	390	390	390	390	390	390	390	390
R-squared	0.156	0.045	0.091	0.054	0.088	0.031	0.094	0.070

Notes: Dependent variable is Δ Real GRDP per capita (in logs).Year difference is 2007 to 2015. Instruments used are district's historical resource abundance in the 1970's and the 1980's (continuous form) and the change in physical resource production for oil, natural gas, and coal. Standard errors are in parentheses. *, **, *** refer to statistical significance at the 10%, 5%,and 1% levels, respectively.

Table 3.3. Summary of OLS and IV regressions: resource dependence and four potential causal channels of growth in per capita income

VARIABLES	**(1)** OLS	**(1′)** GMM	**(2)** OLS	**(2′)** GMM	**(3)** OLS	**(3′)** GMM	**(4)** OLS	**(4′)** GMM
Regression (1): Dep. Variable: ΔManufacturing output								
ΔMining Dependence	0.081	0.319*						
	(0.053)	(0.184)						
ΔMining Revenue			0.183**	0.255**				
			(0.073)	(0.122)				
ΔOilGas Revenue					0.378***	0.385**		
					(0.119)	(0.167)		
ΔCoal Revenue							-0.594***	-0.710*
							(0.209)	(0.367)
Kleibergen-Paap rk F stat		12.266		9.046		16.081		14.164
Hansen *J* Stat, p-value		0.2525		0.1938		0.2404		0.5448
Endog test, p-value		0.0397		0.1325		0.2079		0.7551
Regression (2): Dep. Variable: ΔNet Enrolment Ratio for student in high school								
ΔMining Dependence	0.119***	0.381***						
	(0.044)	(0.119)						
ΔMining Revenue			0.198***	0.282***				
			(0.060)	(0.099)				
ΔOilGas Revenue					0.190***	0.302***		
					(0.064)	(0.106)		
ΔCoal Revenue							0.102	0.206
							(0.137)	(0.229)
Kleibergen-Paap rk F stat		12.266		9.046		16.081		14.164
Hansen *J* Stat, p-value		0.3768		0.3757		0.2775		0.7943
Endog test, p-value		0.0529		0.5067		0.3041		0.5978
Regression (3): Dep. Variable: ΔInstitutional Quality								
ΔMining Dependence	0.700*	2.499***						
	(0.404)	(0.889)						
ΔMining Revenue			1.583***	3.208***				
			(0.585)	(0.629)				
ΔOilGas Revenue					0.986	2.195**		
					(0.698)	(1.003)		

Table 3.3. Continued

VARIABLES	**(1)** OLS	**(1′)** GMM	**(2)** OLS	**(2′)** GMM	**(3)** OLS	**(3′)** GMM	**(4)** OLS	**(4′)** GMM
ΔCoal Revenue							2.667*** (0.967)	5.051*** (1.936)
Kleibergen-Paap rk F stat		12.266		9.046		16.081		14.164
Hansen *J* Stat, p-value		0.0665		0.0615		0.0982		0.0730
Endog test, p-value		0.1681		0.0726		0.2110		0.1954
Regression (4): Dep. Variable: ΔPublic spending on capital								
ΔMining Dependence	0.059 (0.042)	-0.066 (0.140)						
ΔMining Revenue			0.058 (0.082)	0.001 (0.128)				
ΔOilGas Revenue					-0.069 (0.085)	0.015 (0.149)		
ΔCoal Revenue							0.453** (0.182)	0.343 (0.283)
Kleibergen-Paap rk F stat		12.266		9.046		16.081		14.164
Hansen *J* Stat, p-value		0.1269		0.1079		0.4936		0.0291
Endog test, p-value		0.440		0.7246		0.4757		0.7665

Notes: Year difference is 2007 and 2015. Instruments used for all resource dependence measures are district historical resource abundance in the 1970's and the 1980's (continuous form) and the change in physical production for oil, natural gas, and coal. The full results for each causal channel including the other control variables are attached in Appendices (3.2)-(3.8). Standard errors are in parentheses. *, **, *** refers to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.4. Ordered probit results (with and without instruments)

	Dependent Variable: Change in Institutional Quality (ordinal measure)							
Independent Variables	Oprobit	IV Oprobit	Oprobit	IV Oprobit	Oprobit	IV Oprobit	Oprobit	IV Oprobit
ΔMining Dependence	0.779 (0.560)	2.397 (2.210)						
ΔMining Revenue			1.986** (0.834)	2.601 (1.905)				
ΔOilGas Revenue					1.256 (0.886)	0.613 (0.775)		
ΔCoal Revenue							6.033*** (2.189)	12.002** (0.011)
Observations	390	390	390	390	390	390	390	390
Wald Chi2	24.71		31.06		26.52		31.69	
Prob > Chi2	0.0009	0.0000	0.0001	0.0000	0.0004	0.0000	0.0000	0.0000
Pseudo R2	0.0495		0.0548		0.0490		0.0560	
LR chi2		104.72		239.64		291.48		254.65
Log likelihood		21.64		280.65		290.35		529.69
Atanhrho, p-value		0.469		0.713		0.737		0.123
Instruments p-value (1st stage regression)								
- Oil & gas abundance		0.000		0.000		0.000		
- Coal abundance		0.102		0.000				0.000
- Oil production		0.001		0.000		0.000		
- Gas production		0.040		0.002		0.000		
- Coal production		0.428		0.000				0.000

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Note: atanhrho p-value tests for exogeneity of resource dependence measures used in IV Oprobit model.

Table 3.5. Ordered probit results (marginal effects)

	Worsened		Stayed same		Improved	
Variable of interest	M.E	P value	M.E	P value	M.E	P value
ΔMining Dependence	-0.036	0.184	-0.198	0.165	0.235	0.162
ΔMining Revenue	-0.093	0.047	0.501	0.018	0.595	0.017
ΔOilGas Revenue	-0.059	0.178	-0.320	0.159	0.379	0.156
ΔCoal Revenue	-0.281	0.051	-1.527	0.005	1.809	0.006
Observations	390		390		390	

Note: M.E is marginal effect

Table 3.6 reports the step three regressions in which the four candidate transmission channels are added as control variables to the first step regressions. I again place OLS and IV-GMM estimations together for comparison. As before, I start by testing necessary conditions for whether my instruments for resource dependence are still valid. As shown in columns (1')-(4'), the Kleibergen F values range from 8.165 (column 2′) to 14.541 (column 4′), with 3 of four cases above 10. These values suggest the instruments remain relatively strong. According to overidentification tests, the instruments seem to satisfy the exclusion restriction criteria (see the high p values of the Hansen *J* statistics). Finally, the exogeneity of my resource dependence measures can be rejected in almost all cases at the .10 level or better, suggesting that the IV-GMM specifications are preferable to OLS. Perhaps not surprisingly, these validity test results are similar to those found in step one.

Turning to the results of my final step, I first check whether the candidate transmission channels are in fact positively associated with the rate of economic growth within Indonesia over the 2007 to 2015 period. Across all resource dependence measures, growth in real manufacturing output has a positive sign, but is not significant. Similarly a rise in high school enrolment rates has a positive or negative sign across models, but is similarly never significantly associated with growth.

In contrast, the share of public spending on capital appears to be positively associated with local growth for all models as expected, indicating that prioritising capital spending does significantly improve growth in three of four IV-GMM models. For example, the IV-GMM estimation in column (3′) finds that a standard deviation increase in the change in the share of government spending on capital increases per capita income between 2007 and 2015 on average by (0.099 * 0.470 = 0.046) 4.6 per cent. Since the share of public spending on capital was not itself found to be raised by increasing resource dependence in step 2, this would suggest that rising public capital spending does spur growth, but that resource dependence cannot be credited with acting through this particular channel to have raised growth in Indonesia.

Finally, the candidate causal channel that is found to be must robustly positively associated with economic growth is institutional quality. In particular districts that garnered increases in auditor opinion scores between 2007 and 2015 had on average higher growth in per capita incomes. Taking model (3′) as an example, a standard deviation increase in the change in the audit opinion score is associated with a (=1.054*0.0365 = 0.037) 3.7 per cent increase in GRDP between 2007 and 2015. Given that rising resource dependence was found to increase institutional quality in step two, this would suggest that institutional quality may be a promising channel among these four candidates through which resource dependence is raising economic growth in Indonesia.

With respect to control variables outside the four candidates, in step three initial income per capita (in 2006) again has a robust negative effect on subsequent growth rates statistically significant at the 1 per cent level in all models. As in step one, earthquake incidents remain clearly harmful for district growth, while urban status (DURBAN) remains positively associated. Labour force participation rates and initial population remain mostly insignificant.

Finally, I compare the residual direct effect of resource dependence on growth in the third step with what it was before the four candidates were introduced in step 1. The lower panel of Table 3.7 compares the overall effects and calculates the portion explained by the four factors collectively by substracting the coefficient on resource dependence between the first and final step. As reported, the residual direct effect remains quantitatively large meaning that the portion of resource dependence's effects on growth captured by my four causal candidates is limited. The fall in coefficient values only ranges from 0.065 to 0.125, where the largest value refers to the effect of mining dependence on growth under the IV-GMM model. If we consider the change effects captured by my four candidates, according to model (1), for example, the proportion explained is 0.122 or 12.2 per cent. Thus, although institutional quality is shown both to be raised by rising resource dependence, and in turn to raise growth in GRDP per capita, neither it nor the other 3 candidate factors collectively can account for most of the positive effect resource dependence seems to have had on growth in Indonesia after decentralisation.

Table 3.6. OLS and IV regressions: resource dependence, causal channels, and local per capita income

Independent Variables	(1) FD1	(1') IV	(2) FD2	(2') IV	(3) FD3	(3') IV	(4) FD4	(4') IV
ΔMining Dependence	0.595***	1.414***						
	(0.174)	(0.512)						
ΔMining Revenue			0.0224	0.967**				
			(0.255)	(0.390)				
ΔOilGas Revenue					-0.118	1.030**		
					(0.364)	(0.490)		
ΔCoal Revenue							0.492	-0.502
							(0.604)	(0.710)
ΔManufacturing output	0.277	0.0875	0.322	0.0685	0.335	0.0337	0.345	0.270
	(0.219)	(0.170)	(0.229)	(0.158)	(0.231)	(0.151)	(0.233)	(0.221)
ΔNet enrolment ratio	0.014	-0.161	0.112	-0.0598	0.124	-0.048	0.107	0.137
	(0.149)	(0.165)	(0.144)	(0.148)	(0.145)	(0.152)	(0.151)	(0.149)
ΔInstitutions	0.0390***	0.0294**	0.0462***	0.0360**	0.0471***	0.0365**	0.0445***	0.0481***
	(0.0148)	(0.0148)	(0.0155)	(0.0143)	(0.0157)	(0.0151)	(0.0160)	(0.0157)
ΔPublic spending on capital	0.531**	0.316*	0.598**	0.432**	0.595**	0.470**	0.564**	0.593**
	(0.232)	(0.186)	(0.259)	(0.196)	(0.257)	(0.224)	(0.266)	(0.247)
Earthquake	-0.0292**	-0.0287	-0.0292**	-0.0238**	-0.0289**	-0.0293**	-0.0271**	-0.0309**
	(0.0133)	(0.0185)	(0.0120)	(0.0114)	(0.0119)	(0.0122)	(0.0120)	(0.0120)
ΔLabour force partic.rate	0.204	0.187	0.213	0.332**	0.198	0.288*	0.234	0.174
	(0.172)	(0.170)	(0.168)	(0.145)	(0.162)	(0.166)	(0.183)	(0.176)
GRDP per capita, 2006 (in logs)	-0.158***	-0.129***	-0.180***	-0.133***	-0.188***	-0.109**	-0.194***	-0.163***
	(0.0324)	(0.0408)	(0.0313)	(0.0347)	(0.0340)	(0.0474)	(0.0352)	(0.0386)
Population, 2006 (in logs)	-0.00315	0.0187	-0.00943	0.0217	-0.0112	0.0233	-0.00837	-0.00403
	(0.0261)	(0.0197)	(0.0288)	(0.0192)	(0.0290)	(0.0214)	(0.0284)	(0.0265)
DURBAN	0.0747*	0.0866*	0.0741*	0.0682	0.0781*	0.0523	0.0846*	0.0676
	(0.0431)	(0.0448)	(0.0424)	(0.0433)	(0.0405)	(0.0491)	(0.0431)	(0.0436)
DJAVA	0.0586	0.116*	0.0127	-0.0209	0.0177	-0.0299	0.0182	0.00365
	(0.0457)	(0.0670)	(0.0414)	(0.0394)	(0.0429)	(0.0419)	(0.0417)	(0.0425)
Constant	0.914***	0.689***	1.032***	0.726***	1.068***	0.646***	1.071***	0.943***
	(0.203)	(0.202)	(0.228)	(0.171)	(0.240)	(0.201)	(0.230)	(0.228)
Kleibergen F stat		10.893		8.165		12.926		14.541
Hansen *J*, p value		0.3463		0.1168		0.2059		0.3340
Endogeneity, p value		0.1872		0.0610		0.0472		0.0903
Observations	390	390	390	390	390	390	390	390
R-squared	0.204	0.104	0.154	0.100	0.154	0.086	0.157	0.143

Table 3.7. Residual Effects

	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
VARIABLES	FD1	IV	FD2	IV	FD3	IV	FD4	IV
Coefficients in the First Step (A)								
ΔMining Dependence	0.678***	1.539***						
	(0.191)	(0.483)						
ΔMining Revenue			0.211	1.032***				
			(0.272)	(0.381)				
ΔOilGas Revenue					0.0385	1.119**		
					(0.384)	(0.494)		
ΔCoal Revenue							0.672	-0.642
							(0.583)	(0.699)
Coefficients in the Third Step (B)								
ΔMining Dependence	0.595***	1.414***						
	(0.174)	(0.512)						
ΔMining Revenue			0.0224	0.967**				
			(0.255)	(0.390)				
ΔOilGas Revenue					-0.118	1.030**		
					(0.364)	(0.490)		
ΔCoal Revenue							0.492	-0.502
							(0.604)	(0.710)
Residual Effects (A) – (B)	0.083	0.125		0.065		0.089		

Notes: For Table 3.6. and 3.7. Dependent variable is Δ Real GRDP per capita (in logs).Year difference is 2007 and 2015. Instruments used for all resource dependence measures are districts historical resource abundance in the 1970's and the 1980's (continuous form) and the physical natural resources production for oil, natural gas, and coal minerals. Standard errors in parentheses. *, **, *** statistically significant at 10%, 5%, and 1%, respectively.

3.4.2 Institutional Quality Effects

3.4.2.1 Split sample results: districts with stronger vs. weaker institutions

In this section, I provide the results of testing the auxiliary hypothesis in the resource curse literature that resource dependence aids growth for jurisdictions that already have good institutions, but harms growth for those who do not. Following the strategy explained in Section 3.3.2.2, I start with the split sample strategy which shows the overall effect of changes in resource dependence between 2007 and 2015 on growth in local income per capita for districts that had stronger or weaker institutions in 2006. As before, I include OLS and IV-GMM FD estimators. Results are shown in Table 3.8 for OLS, and Table 3.9 for IV-GMM.

As shown in columns (1)-(4) of Table 3.8 most resource dependence coefficients are positive for districts with stronger institutions, but none is significant. For districts with weaker institutions, the coefficients are indeed negative for two of four models, but not significant. They are positive for the other two models, significantly so for model (1). Thus without instruments, I find no evidence in support of the hypothesis that resource dependence is worse for growth in districts with poorer institutional quality.

I next turn to Table 3.9 that reports analogous results under IV-GMM, addressing as before potential possible endogeneity of each resource dependence measure. I begin by checking whether my continuous form of historical resource abundance plus physical resources production are valid instruments for the split samples. For stronger institution districts, the Kleibergen-Paap rank F statistics range from 13.802 to 243.487, suggesting strong instruments. For weaker institution districts, the F statistic is only 1.021 for model (1), but for in excess of 10 for the other three measures. The p-values of Hansen *J* tests are well above p values of .10 in all models, consistent with exogeneity of my instruments. Using both criteria, my instruments pass necessary conditions for validity in 7 of 8 cases. With respect to exogeneity of my resource dependence measures, this can be rejected only for model (4') among weaker institution districts.

Discussing IV results nonetheless, as in Table 3.9, I do not find evidence that resource dependence has more positive effects on growth in districts with higher institutional quality than in districts with lower institutional quality. The four resource dependence coefficients in stronger institution districts in columns (1')-(4') are mostly positive but never significant. In contrast, rising natural resource dependence significantly raises income growth in two of four models among the weak institutions sample group (see Columns (5') and (6')). Take for example, the case of rising government dependence on mining revenues, since it satisfies all criteria of instrument validity, exogeneity, and endogeneity. A standard deviation increase in the change in mining revenue dependence, on average, increases real income per capita in weaker institution districts between 2007 and 2016 by (0.081*1.333 = 0.109) 10.9 per cent. Thus using split sample strategy, I do not find evidence that resource dependence is a "conditional blessing" when institutions are strong and a "conditional curse" when they are weak.

Before I move to a second strategy for testing the conditional hypothesis of resource effects, I also try an alternative institutional quality measure, a *local governance performance index*, to check whether the previous results hold. As foreshadowed in Section 3.3.2.2., this index is more comprehensive but lacks values for years prior to 2010. As a consequence, I use the change in quantity outcomes between 2011-2015, with 2010 index values used to split the sample.

Estimations reported in Table 3.10 summarise OLS results, and those in Table 3.11 for IV-GMM results. In general, my findings are similar to those in Table 3.8, where if anything higher local government dependence on total mining revenues, or oil and gas revenues in particular, are more likely to aid growth in per capita income in weaker institution districts. Moving to IV-GMM estimation results in Table 3.11, my instruments are weaker in models (1'), (4'), (5') and (8'), but again exogenous. Regarding exogeneity of resource dependence, p-values across most specifications are greater than 0.10, except for models (1') and (3'), where exogeneity is rejected.

Only in Table 3.11, with the more comprehensive institutional quality index over fewer years, and instruments used, is some evidence found that partially supports the "conditional curse/blessing' hypothesis. Here the coefficient on resource dependence appears larger for districts with stronger institutions, with values greater than 1, while in weaker institution districts the magnitude is generally less than 0.5. Even here, however, instrument validity is questionable for models (1') and (4') for both groups of districts, and while the instruments pass validity tests for model (2'), exogeneity of resource dependence cannot be rejected. Thus only for model (3'), the share of government revenues from oil and gas, does resource dependence seem to raise growth more in strong institution districts.

In summary, whether with a limited institutional quality (capacity) measure over a longer period, or more comprehensive performance measure over a shorter period, I do not find much evidence from the split sample method that districts who begin with stronger institutions find a stronger growth benefit from resource dependence.

Table 3.8. FD-OLS results for both district sample groups with stronger and weaker initial institutions

	Stronger institutions				Weaker institutions			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔMining Dependence	0.0621				1.085***			
	(0.170)				(0.296)			
ΔMining Revenue		0.488				-0.187		
		(0.357)				(0.423)		
ΔOilGas Revenue			0.547				-0.409	
			(0.371)				(0.686)	
ΔCoal Revenue				-1.016				0.447
				(1.112)				(0.654)
Earthquake	-0.00824	-0.00861	-0.00945	-0.00907	-0.0332	-0.0512	-0.0504	-0.0474
	(0.0114)	(0.0106)	(0.0105)	(0.0110)	(0.0333)	(0.0331)	(0.0328)	(0.0324)
ΔLabour force partic.rate	0.793***	0.903***	0.914***	0.806***	-0.00115	-0.132	-0.137	-0.0920
	(0.267)	(0.241)	(0.242)	(0.250)	(0.225)	(0.242)	(0.233)	(0.264)
GRDP per capita, 2006 (in logs)	-0.160***	-0.142***	-0.139***	-0.165***	-0.114***	-0.141***	-0.164***	-0.156***
	(0.0483)	(0.0442)	(0.0443)	(0.0485)	(0.0407)	(0.0404)	(0.0518)	(0.0453)
Population, 2006 (in logs)	0.0306	0.0310	0.0316	0.0313	0.00452	0.00484	0.00294	0.00679
	(0.0294)	(0.0295)	(0.0294)	(0.0295)	(0.0316)	(0.0351)	(0.0353)	(0.0349)
DURBAN	0.0749	0.0608	0.0581	0.0749	0.0998*	0.0604	0.0729	0.0767
	(0.0610)	(0.0582)	(0.0581)	(0.0611)	(0.0593)	(0.0654)	(0.0632)	(0.0642)
DJAVA	0.0993	0.0739	0.0656	0.0849	0.0163	-0.0327	-0.0183	-0.0278
	(0.0601)	(0.0546)	(0.0552)	(0.0571)	(0.0973)	(0.0937)	(0.0961)	(0.0930)
Constant	0.680***	0.624***	0.620***	0.702***	0.765***	0.944***	1.033***	0.974***
	(0.166)	(0.165)	(0.165)	(0.178)	(0.217)	(0.244)	(0.276)	(0.246)
Observations	195	195	195	195	195	195	195	195
R-squared	0.230	0.245	0.248	0.231	0.206	0.068	0.073	0.070

Notes: Dependent variable is Δ Real GRDP per capita (in logs).Stronger and weaker institutions refer to initial level of institutional quality in 2006. Year difference is 2007 and 2015. Standard errors in parentheses. *, **, *** refers to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.9. IV-GMM results for both district sample groups with stronger and weaker initial institutions

	Stronger institutions				Weaker institutions			
VARIABLES	(1')	(2')	(3')	(4')	(5')	(6')	(7)	(8')
ΔMining Dependence	0.346				3.576***			
	(0.316)				(1.148)			
ΔMining Revenue		0.317				1.333**		
		(0.244)				(0.657)		
ΔOilGas Revenue			0.462				1.574	
			(0.291)				(1.079)	
ΔCoal Revenue				0.0996				-0.294
				(0.834)				(0.784)
Earthquake	-0.00773	-0.00541	-0.00750	-0.00645	0.00293	-0.0305	-0.0395	-0.0517
	(0.0123)	(0.0102)	(0.0103)	(0.0109)	(0.0725)	(0.0302)	(0.0323)	(0.0320)
ΔLabour force partic.rate	0.586**	0.777***	0.739***	0.767***	0.322	0.122	0.0311	-0.194
	(0.259)	(0.175)	(0.184)	(0.241)	(0.271)	(0.254)	(0.278)	(0.246)
GRDP per capita, 2006 (in logs)	-0.155***	-0.167***	-0.151***	-0.164***	-0.0810	-0.0765	-0.0228	-0.130***
	(0.0406)	(0.0363)	(0.0448)	(0.0474)	(0.0543)	(0.0504)	(0.0938)	(0.0497)
Population, 2006 (in logs)	0.0346	0.0348	0.0312	0.0294	0.00734	0.0413	0.0399	0.0115
	(0.0284)	(0.0277)	(0.0282)	(0.0288)	(0.0376)	(0.0271)	(0.0308)	(0.0336)
DURBAN	0.0948*	0.0974**	0.0816	0.0839	0.197***	0.0419	0.0128	0.0622
	(0.0550)	(0.0492)	(0.0530)	(0.0592)	(0.0735)	(0.0607)	(0.0813)	(0.0620)
DJAVA	0.107*	0.0742	0.0645	0.103*	0.134	-0.116	-0.143	-0.0457
	(0.0564)	(0.0487)	(0.0494)	(0.0541)	(0.141)	(0.0852)	(0.0939)	(0.0923)
Constant	0.628***	0.680***	0.661***	0.693***	0.439	0.482**	0.328	0.873***
	(0.163)	(0.154)	(0.162)	(0.174)	(0.324)	(0.245)	(0.362)	(0.257)
Kleibergen-Paap rk F statistics	22.283	14.848	13.802	243.487	1.021	64.885	126.197	17.760
Hansen *J* Stat, p-value	0.5964	0.6028	0.3799	0.4427	0.6972	0.4339	0.3990	0.4017
Endog test, p-value	0.3780	0.2787	0.4451	0.0905	0.0165	0.0588	0.0243	0.2778
Observations	195	195	195	195	195	195	195	195
R-squared	0.208	0.237	0.242	0.228	-0.531	-0.032	-0.077	0.059

Notes: Dependent variable is Δ Real GRDP per capita (in logs).Stronger and weaker institutions refer to initial level of institutional quality in 2006. Year difference is 2007 and 2015. Instruments used are districts historical resource abundance in the 1970's and the 1980's (continuous form) and the physical natural resources production for oil, natural gas, and coal minerals. Standard errors are in parentheses. *, **, *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3.10. FD-OLS estimates between stronger and weaker institutions among districts, alternative institutional quality measure

	Stronger institutions				Weaker institutions			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔMining Dependence	0.0410				-0.0237			
	(0.586)				(0.0974)			
ΔMining Revenue		-0.579				0.197**		
		(0.812)				(0.0971)		
ΔOilGas Revenue			-0.585				0.197**	
			(0.844)				(0.0942)	
ΔCoal Revenue				-0.171				-0.0430
				(1.392)				(0.252)
Earthquake	-0.0232*	-0.0216*	-0.0215*	-0.0228*	-0.0118**	-0.0127***	-0.0125***	-0.0115**
	(0.0127)	(0.0120)	(0.0119)	(0.0120)	(0.00474)	(0.00460)	(0.00462)	(0.00482)
ΔLabour force partic.rate	0.393	0.445	0.439	0.399	-0.106	-0.0981	-0.0991	-0.108
	(0.407)	(0.405)	(0.403)	(0.397)	(0.0679)	(0.0644)	(0.0642)	(0.0663)
GRDP per capita, 2010 (in logs)	-0.00519	-0.0366	-0.0426	-0.00455	-0.0350***	-0.0251*	-0.0246*	-0.0345***
	(0.0353)	(0.0365)	(0.0416)	(0.0373)	(0.0119)	(0.0145)	(0.0147)	(0.0123)
Population, 2010 (in logs)	-0.0642*	-0.0667*	-0.0650*	-0.0653*	0.00195	0.00327	0.00333	0.00161
	(0.0377)	(0.0347)	(0.0330)	(0.0343)	(0.00624)	(0.00602)	(0.00600)	(0.00631)
DURBAN	-0.0373	-0.0178	-0.0135	-0.0386	-0.00686	-0.00743	-0.00834	-0.00610
	(0.0670)	(0.0487)	(0.0430)	(0.0658)	(0.0230)	(0.0225)	(0.0224)	(0.0227)
DJAVA	0.0666*	0.0898*	0.0885*	0.0672*	0.0314**	0.0246*	0.0242*	0.0324**
	(0.0380)	(0.0489)	(0.0480)	(0.0386)	(0.0138)	(0.0138)	(0.0137)	(0.0139)
Constant	0.634**	0.751**	0.764**	0.638***	0.292***	0.251***	0.249***	0.291***
	(0.245)	(0.297)	(0.321)	(0.195)	(0.0568)	(0.0617)	(0.0623)	(0.0574)
Observations	191	191	191	191	192	192	192	192
R-squared	0.035	0.048	0.047	0.035	0.081	0.101	0.101	0.080

Notes: Dependent variable is Δ Real GRDP per capita (in logs). Stronger and weaker institutions refer to initial level of institutional quality in 2010 based on *local governance performance index*. The year difference is 2011 to 2015. Standard errors are in parentheses. *, **, *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.11. IV-GMM estimates comparing districts with stronger and weaker institutions. Years investigated 2011-2015

	Stronger institutions				Weaker institutions			
VARIABLES	(1')	(2')	(3')	(4')	(5')	(6')	(7')	(8')
ΔMining Dependence	2.273*				0.0949			
	(1.269)				(0.163)			
ΔMining Revenue		1.495***				0.238*		
		(0.365)				(0.139)		
ΔOilGas Revenue			**1.905*****				0.258*	
			(0.498)				(0.142)	
ΔCoal Revenue				0.319				0.192
				(1.814)				(1.977)
Earthquake	-0.0432	-0.0203	-0.0243*	-0.0212*	-0.0139***	-0.0142***	-0.0130***	-0.0119**
	(0.0276)	(0.0126)	(0.0132)	(0.0113)	(0.00527)	(0.00449)	(0.00454)	(0.00493)
ΔLabour force partic.rate	0.138	0.241	0.224	0.379	-0.127*	-0.104*	-0.0984	-0.102
	(0.499)	(0.387)	(0.390)	(0.392)	(0.0697)	(0.0598)	(0.0624)	(0.0689)
GRDP per capita, 2010 (in logs)	0.0507	0.0388	0.0980*	-0.0149	-0.0467***	-0.0275*	-0.0220	-0.0340**
	(0.0549)	(0.0426)	(0.0577)	(0.0353)	(0.0110)	(0.0149)	(0.0154)	(0.0140)
Population, 2010 (in logs)	-0.0125	-0.0259	-0.0588	-0.0508*	0.00464	0.00500	0.00386	0.00177
	(0.0269)	(0.0280)	(0.0380)	(0.0266)	(0.00697)	(0.00589)	(0.00595)	(0.00639)
DURBAN	-0.0102	-0.0241	-0.103	-0.0131	-0.00814	-0.0132	-0.0110	-0.00807
	(0.0588)	(0.0569)	(0.0842)	(0.0528)	(0.0232)	(0.0220)	(0.0221)	(0.0236)
DJAVA	0.0563	0.00371	-0.00660	0.0638*	0.0347**	0.0197	0.0207	0.0329**
	(0.0404)	(0.0350)	(0.0384)	(0.0382)	(0.0155)	(0.0140)	(0.0144)	(0.0152)
Constant	0.0477	0.247*	0.259*	0.578***	0.319***	0.253***	0.237***	0.288***
	(0.213)	(0.150)	(0.153)	(0.153)	(0.0544)	(0.0647)	(0.0659)	(0.0635)
Kleibergen-Paap rk	2.673	41.769	44.835	0.882	4.478	18.940	30.436	0.813
Hansen *J* Stat, p-value	0.8022	0.4960	0.2960	0.5359	0.1708	0.4663	0.5630	0.3224
Endog test, p-value	0.0353	0.2287	0.0551	0.6511	0.5156	0.5926	0.6357	0.8437
Observations	191	191	191	191	192	192	192	192
R-squared	-0.191	-0.140	-0.181	0.031	0.045	0.098	0.099	0.077

Notes: Dependent variable is Δ Real GRDP per capita (in logs). Stronger and weaker institutions refer to initial level of institutional quality in 2010 based on a *local governance performance index*. The year difference is 2011 to 2015. Instruments used are districts' historical resource abundance in the 1970's and 1980's (continuous form) and change in the physical resource production for oil, natural gas, and coal. Standard errors are in parentheses. *, **, *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.2.2 *Interactions between resource dependence and institutions*

In the final part of this section, I use a second approach to test the conditional effects hypothesis. Here I do not split the sample of districts, but instead test for interaction effects between the four measures of resource dependence and institutional quality in their effects on district per capita growth. In doing so, I use initial levels of institutional quality either in 2006 (Ins06) or 2010 (Ins10). To begin, I discuss the estimation results for the interaction term for my longer running, but less comprehensive measure of district government institutional quality, which again follows the periods 2007 and 2015. I concentrate here on the coefficients of interaction (RD1*Ins06 through RD4*Ins06). This tests whether the effect of, say mining dependence, on real income per capita depends on the initial level of institutional quality in 2006.

I begin with IV validity tests for Table 3.12. For comparison, IV-GMM results are also provided across columns which also show the tests of instruments validity and endogeneity of the main regressor. Here, the p-values of Hansen *J* tests fail to reject the exogeneity of my instruments in all models based on the 5% significance level, whereas the Kleibergen-Paap F statistic is also close to the required rule of thumb for columns (1’) and (2’) and exceeds it in column (3’). Endogeneity tests show that models (3’) and (4’) suffer from endogeneity, but cannot reject exogeneity for models (1’) and (2’), suggesting OLS is the preferred estimator.

Moving to results in Table 3.12, as shown in column (1), with initial institutional quality its minimum value, a change from 0 to 100% share of mining in total GRDP is associated with an increase in income per capita on average of 223 per cent between 2007 and 2015, significant at the 5 % level. A positive main effect is also found for coal revenue dependence, but is not significant nor are the main effects in models (2) and (3), though the signs are negative. Relevant here, however, the coefficients on the interaction term in columns (1) and (4) are negative and significant, suggesting higher institutional quality lowers the growth benefits of resource dependence. In particular, for a district with average institutional quality in 2006 (2.510), the overall effect of a change from 0 to 1 in mining dependence would be only a (2.226 - .624 (2.510) = .660) 66 per cent increase in income per capita.

For the rest of the models, however, initial institutional quality does not seem to influence the effect that resource dependence has on growth. However, as I fail to prove that my instruments are valid as indicated in Table 3.12, I put greater weight on the OLS estimates.

Finally, I present the results which use the same strategy as before but now with the more comprehensive quality measure available between 2011 and 2015, and use institutional performance in 2010 as a baseline. Table 3.13. presents coefficient estimates under OLS. I find that the main effect of resource dependence on growth is not significant across models (1) to (4). More importantly, the interaction terms, RD1*Ins10 throughout RD4*Ins10, are no longer significant, though still negatively signed. Thus I cannot reject the null hypothesis that initial comprehensive institutional quality has no effect on the extent to which resource dependence causes growth.

If we move to IV-GMM specifications, again although overidentification tests are consistent with excluded instruments being independent from errors, my instruments produce very low F statistics far below the recommended threshold of 10. This indicates that the instruments are weak. Persevering with them, I find that endogeneity tests fail to reject exogenous resource dependence in all models, suggesting that OLS estimation may be valid.

Nonetheless, if I consider IV-GMM results for the better but shorter institutional quality measure, I find that the interaction between resource dependence and prior institutional quality is positive and significant in three of four cases. This could indicate the evidence for a “contingent curse”. However, I also notice that the instruments are weak and endogeneity is not indicated in any specification. Thus, whether I use a split sample or interaction term approach, (weak) instruments or OLS, and a longer/narrower or shorter/broader measure of institutional quality, I find little or weak evidence in support of the contingency hypothesis that resource dependence raises growth for stronger institution districts, and lowers growth for weaker institution districts.

Table 3.12. OLS and IV regression estimates with interaction terms, 2007-2015

	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
VARIABLES	FD	IV	FD2	IV	FD3	IV	FD4	IV
ΔMining Dependence	2.226***	3.579***						
	(0.808)	(1.230)						
ΔMining Revenue			-0.178	0.903				
			(0.853)	(0.972)				
ΔOilGas Revenue					-0.773	1.595		
					(1.013)	(1.317)		
ΔCoal Revenue							1.926	0.309
							(1.318)	(1.069)
Earthquake	-0.0274**	-0.014	-0.0294**	-0.020*	-0.0294**	-0.029**	-0.0299**	-0.034***
	(0.0138)	(0.018)	(0.0119)	(0.012)	(0.0118)	(0.012)	(0.0121)	(0.012)
ΔLabour force partic.rate	0.240	0.193	0.237	0.225	0.261	0.188	0.206	0.059
	(0.170)	(0.161)	(0.190)	(0.168)	(0.192)	(0.170)	(0.198)	(0.181)
GRDP per capita, 2006 (in logs)	-0.121***	-0.136***	-0.135***	-0.147***	-0.142***	-0.080*	-0.166***	-0.137***
	(0.0294)	(0.028)	(0.0294)	(0.028)	(0.0350)	(0.048)	(0.0342)	(0.037)
Population, 2006 (in logs)	0.0154	0.025	0.0153	0.034**	0.0134	0.033*	0.0124	0.015
	(0.0193)	(0.018)	(0.0210)	(0.017)	(0.0211)	(0.019)	(0.0214)	(0.021)
Ins06	-0.00196	0.014	-0.0279	-0.026	-0.0127	-0.055	-0.0129	-0.016
	(0.0187)	(0.028)	(0.0260)	(0.023)	(0.0291)	(0.036)	(0.0249)	(0.026)
DURBAN	0.0595	0.099***	0.0506	0.090**	0.0490	0.039	0.0620	0.049
	(0.0399)	(0.038)	(0.0414)	(0.036)	(0.0405)	(0.045)	(0.0427)	(0.043)
DJAVA	0.0711	0.080	0.0335	0.022	0.0265	-0.003	0.0375	0.013
	(0.0445)	(0.049)	(0.0426)	(0.039)	(0.0429)	(0.042)	(0.0422)	(0.044)
RD1*Ins06	-0.624**	-0.986**						
	(0.280)	(0.434)						
RD2*Ins06			0.172	-0.278				
			(0.333)	(0.370)				
RD3*Ins06					0.416	-0.300		
					(0.382)	(0.422)		
RD4*Ins06							-0.759*	-0.678
							(0.448)	(0.506)
Constant	0.713***	0.639***	0.867***	0.771***	0.870***	0.651***	0.959***	0.873***
	(0.149)	(0.168)	(0.173)	(0.149)	(0.176)	(0.166)	(0.182)	(0.180)

Table 3.12. Continued

VARIABLES	(1) FD	(1') IV	(2) FD2	(2') IV	(3) FD3	(3') IV	(4) FD4	(4') IV
Kleibergen-Paap rk F stat		9.615		8.357		23.26		3.736
Hansen *J* Stat, p-value		0.163		0.067		0.494		0.373
Endog test, p-value		0.191		0.453		0.097		0.082
Observations	390	390	390	390	390	390	390	390
R-squared	0.203	0.150	0.097	0.075	0.104	0.032	0.106	0.074

Notes: Dependent variable is Δ Real GRDP per capita (in logs). Ins06 is the level of quality of institutions in 2006 for each district based on the audit opinion score of the Indonesia Audit Board. The interaction variable is denoted by RD*Ins06 , where RD1-RD4 are each measure of resource dependence (ΔMining Dependence, ΔMining Revenue, ΔOilGas Revenue, ΔCoal Revenue). The year difference is 2007 to 2015. Instruments used are districts' historical resource abundance in the 1970's and the 1980's (continuous form) and the change in physical natural resource production for oil, natural gas, and coal. Interactions of these variables with *Ins06* are also used as instruments for RD1*Ins06-RD4*Ins06. The IV technique uses IVREG2 provided by Schaffer, et al. (2003). Standard errors are in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.13. OLS and IV regression estimates with interaction terms, periods 2011-2015

VARIABLES	(1) FD	(1’) IV	(2) FD2	(2’) IV	(3) FD3	(3’) IV	(4) FD4	(4’) IV
ΔMining Dependence	0.139	-2.606						
	(0.566)	(1.645)						
ΔMining Revenue			0.404	-0.485				
			(0.712)	(0.643)				
ΔOilGas Revenue					0.216	-0.437		
					(0.596)	(0.564)		
ΔCoal Revenue							3.674	7.089
							(3.238)	(8.667)
Earthquake	-0.0175***	-0.020**	-0.0175***	-0.015***	-0.0173***	-0.018***	-0.0178***	-0.018***
	(0.00563)	(0.010)	(0.00548)	(0.005)	(0.00547)	(0.006)	(0.00593)	(0.006)
ΔLabour force partic.rate	0.0650	0.019	0.0681	0.012	0.0652	0.041	0.0698	0.058
	(0.151)	(0.155)	(0.150)	(0.139)	(0.150)	(0.142)	(0.150)	(0.149)
GRDP per capita, 2010 (in logs)	-0.0148	-0.000	-0.0273	0.006	-0.0297	0.036	-0.0151	-0.025
	(0.0189)	(0.021)	(0.0189)	(0.020)	(0.0206)	(0.027)	(0.0198)	(0.019)
Population, 2010 (in logs)	-0.0264*	-0.006	-0.0277*	-0.004	-0.0275*	-0.019	-0.0265*	-0.022*
	(0.0145)	(0.010)	(0.0158)	(0.011)	(0.0156)	(0.014)	(0.0140)	(0.012)
Ins10	0.0883**	0.015	0.0770**	0.056	0.0798**	0.086**	0.0917***	0.088**
	(0.0375)	(0.029)	(0.0333)	(0.036)	(0.0338)	(0.040)	(0.0347)	(0.037)
DURBAN	-0.0135	0.032	-0.0102	0.001	-0.00835	-0.031	-0.0128	-0.006
	(0.0353)	(0.026)	(0.0301)	(0.028)	(0.0283)	(0.037)	(0.0331)	(0.029)
DJAVA	0.0405*	0.064***	0.0545**	0.004	0.0534**	-0.006	0.0386*	0.036*
	(0.0232)	(0.024)	(0.0271)	(0.020)	(0.0266)	(0.024)	(0.0227)	(0.021)
RD1*Ins10	-0.0545	1.554**						
	(0.319)	(0.785)						
RD2*Ins10			-0.280	0.531*				
			(0.466)	(0.292)				
RD3*Ins10					-0.202	0.591**		
					(0.418)	(0.273)		
RD4*Ins10							-1.390	-2.101
							(0.991)	(2.944)
Constant	0.188*	0.138	0.264*	0.058	0.265*	-0.024	0.182*	0.205**
	(0.0989)	(0.102)	(0.140)	(0.105)	(0.149)	(0.118)	(0.0990)	(0.104)

Table 3.13. Continued

VARIABLES	(1) FD	(1') IV	(2) FD2	(2') IV	(3) FD3	(3') IV	(4) FD4	(4') IV
Kleibergen-Paap rk F stat		0.819		0.788		0.401		0.090
Hansen *J* Stat, p-value		0.330		0.358		0.262		0.758
Endog test, p-value		0.949		0.527		0.218		0.495
Observations	383	383	383	383	383	383	383	383
R-squared	0.038	-0.156	0.044	-0.055	0.043	-0.071	0.040	0.019

Notes: Dependent variable is Δ Real GRDP per capita (in logs). Ins10 is the level of quality of institutions in 2010 for each district based on the index of local government performance supplied by the Ministry of Home Affairs, the Republic of Indonesia. The interaction variable is denoted by RD*Ins10, where RD1-RD4 are the sequence of each measure, ΔMining Dependence, ΔMining Revenue, ΔOilGas Revenue, ΔCoal Revenue. The year difference is 2011 to 2015. Instruments used are districts' historical resource abundance in the 1970's and the 1980's (continuous form) and the change in physical resource production for oil, natural gas, and coal. Instruments used are districts' historical resource abundance in the 1970's and the 1980's (continuous form) and the change in physical natural resource production for oil, natural gas, and coal. Interactions of these variables with *Ins10* are also used as instruments for RD1*Ins10-RD4*Ins10. The IV technique uses IVREG2 provided by Schaffer, et al. (2003). Standard errors are in parentheses. *, **, *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.5 Discussion and Conclusions

In this chapter I have examined whether the potential causal channels identified in the resource curse/blessing literature can account for the positive effects of resource dependence on per capita income in Indonesia. Using a three step strategy, I have found several interesting things.

First, using a slightly narrower time frame in my first step, I again find that (non-coal) resource dependence is positively associated with per capita income in post-decentralisation Indonesia. By using an OLS approach, I find that three out of four resource dependence measures have positive coefficients, though only mining's share of GRDP is significant at the 1 per cent level. Instrumenting for endogeneous resource dependence using historical resource abundance and change in physical output, I find significant positive effects for three of four resource dependence measures, leaving only coal revenue dependence not significant. These results are consistent with those found in the previous chapter which used the same regression equation and estimation techniques, but starting from 2006 rather than 2007. The positive benefits of the discovery of a large natural resource endowments, such as oil, or of high dependence on oil exports in developing countries has indeed been found by several studies (Larsen, 2006; Yates, 2006), but is still a debatable topic in the literature (Ablo, 2015).

As this study covers a period of time in which decentralisation has moved government function to district level, several resource-based regions where mining production sites are situated have benefited greatly from activity associated with resource extraction, and from rent allocation compared to districts that have fewer mining activities. The higher rent allocation occurs according to Indonesia's natural resource rent sharing law, whereby resource-rich districts are allocated higher revenues by Indonesia's national government in their annual budgets compared to less resource-rich ones. This higher resource activity and rents seems to improve district income per capita on average.

Second, I have found that most of my resource dependence measures have positively affected candidate factors often linked to growth in the resource curse/blessing literature. Beginning with the positive effect of resource dependence (other than coal revenue dependence) on the size of manufacturing output, my results contrast to the Dutch disease prediction of the resource curse literature. This positive association confirms some previous studies on Indonesia (see Usui (1997), Asanuma (2008), and Feryawan (2011)). These previous studies used descriptive analysis to explore the occurence of the Dutch disease using provincial or district level data, but they did not use panel regression methods or recent periods. This positive association of resource dependence with manufacturing may be caused by higher induced demand for resource-related manufactured good or be caused by well implemented macro policies implemented during the 1970's oil bonanza, which protected a number of manufacturing firms deemed to produce nationally strategic products (part of an import-substitution strategy). Another possible explanation is the investment strategy driving Indonesian technocrats to attract foreign and domestic capital inflows to expand non-natural resource tradable sectors.[79] This investment strategy has flourished during the decentralisation era where each local government is pressured to find non-resource sources of income to accelerate and maintain development. Those districts receiving greater resource rents may have been better able to attract manufacturing ventures, but the fact that coal dependence has negative effects on manufacturing size may signal that a Dutch disease phenomenon occurs at the local level.[80]

I similarly find that (non-coal) resource dependence is positively rather than negatively associated with enrolment rates in secondary schools (including vocational schools). This result is contrary to the hypothesis that countries that experience a boom in natural resources are likely to have lower school enrolment rates, or higher dropout rates, as mining creates an incentive for young people to leave school for well paid jobs in this sector (Black et al., 2005; Gylfason, 2001). This contrary finding may be due to an increase in the supply of public education as local governments under decentralisation have more responsibility to provide basic education, which in turn may lead to higher local participation in schooling. Another possibility is that as district incomes have grown and the economy has developed, completing secondary education may be becoming viewed by employees and young people as "a basic need" to access job markets. Thus there may have been offsetting reasons why the demand for education has increased.

Again of some surprise, I find evidence of a positive association between district resource dependence and quality of local institutions. Many previous studies at the country level, either using cross-section or panel investigations, have found a negative correlation between natural resource wealth and institutional quality (generally identified using rule of

[79] This policy is discussed further by Asanuma (2008), Hill (1992), and by Hill, Resosudarmo and Vidyattama (2008).

[80] As shown in descriptive statistics above, as local district governments have become less dependent on the revenues from the oil and gas sector (though not coal) we can see that manufacturing size, on average, has increased by 0.046188 (or IDR 461.88 billions or equal to NZD 48 millions) over the nine year period.

law or government effectiveness measures). In contrast, I find that in almost all models, whether using OLS or IV-GMM models, and cardinal or ordered probit approaches, there is a positive impact of resource dependence measures, including coal, on measured quality of district-level institutions.[81] Explanations to justify this finding are quite tentative given that previous country-level studies have often found the opposite. However, some studies I have cited as references have found a positive association, or found no link (Brunnschweiler, 2008; Brunnschweiler and Bulte, 2008; Alexeev and Conrad, 2009; di John, 2011). As my institutional quality variable uses audit opinion scores taken from the Indonesia Audit Board based on the quality of local financial administration in each district, my findings might suggest that resource dependent districts are using the resource rents they receive to improve their administrative capacity, perhaps spurred on to do so because of additional responsibilities assigned to districts under decentralisation (Cust and Poelhekke, 2015).

When I turn to ask if these four candidate causal channels actually raise growth rates in Indonesia, I find mixed evidence. First, I find a significant positive impact of increases in institutional quality on changes in per capita income. These results are consistent with the literature that says better institutions are strongly associated with better economic and development outcomes, especially where political power is decentralised (Acemoglu, Johnson, and Robinson, 2005). An increase in democracy is often associated with political redistribution of decision making power to the majority of the population, or in the case of decentralisation to sub-national bodies. Indonesia has implemented decentralisation administratively beginning in 2001, and by 2005 has effectively implemented it, as marked by widespread local district elections held every 5 years. Similarly, I also find that public spending on capital positively affects income growth on average. Since in the second step I fail to find a positive association between resource dependence and capital spending (other than coal revenue dependence), this would suggest that local public spending has raised growth in Indonesia, but that resource dependence has not acted to boost such spending.

In contrast, I do not find evidence that growth in Indonesia has been driven by rising school enrolment rates, or higher manufacturing output *per se*. Given the four candidate channels aforementioned in this investigation, I have conclude that while most channels have been positively affected by rising resource dependence, of these only rising institutional

[81] I provide scatterplots, with a regression line, in Appendix O, Fig 4 and 5, which show the relationship between the average change in district GRDP per capita (with or without log transformation) and the average of institutional quality between 2007 and 2015.

quality in turn significantly affects growth in per capita income. At the same time, my four candidate causal mechanisms together account for only a small part of resource dependence's positive effects on growth. In particular, the estimated positive coefficients of the direct remaining effects of resource dependence were only slightly reduced when the four candidate channels were controlled. Thus, I do find that resource dependence has worked through institutional quality to raise district per capita income in Indonesia, but that it has mostly worked through other means not here identified.[82]

Still with institutional quality, I also test the auxiliary hypothesis that resource dependence does not affect institutional quality, but instead has effects on growth that are determined by pre-existing institutional quality. To test this, I split my sample distinguishing districts with stronger and weaker institutions in 2006 and repeat my first step regression. Using my (limited) institutions measure for the change between 2007 and 2015, I find that resources have been if anything a greater blessing for districts with weaker institutions than those with stronger ones, though this was not robust across the four different measures of resource dependence. When I move to the shorter period of 2011 and 2015 in order to use more comprehensive institutions measure, I again in almost all cases find that resource dependence effects are no stronger for better institution districts than weaker institution districts.

I find a similar lack of support for the 'conditional curse' hypothesis when I instead include an interaction term between change in resource dependence and initial level of institutional quality. In general, the interaction term is not significant, or in some cases is negative and significant. When I repeat this exercise for fewer years using a more comprehensive district government performance measure, the interaction term is never significant without instruments, though it is significantly positive with instruments that are extremely weak and exogeneity is rejected.

[82] A few studies discuss service sector GDP as one channel to explain a resource blessing (Cust and Poelhekke, 2015; Cust and Rusli, 2016). For Indonesia in particular, another channel is probably connected with the high migrant movements as resource-rich provinces became a magnet to those seeking better incomes (Hill, Resosudarmo, and Vidyattama, 2008). This pattern would probably contribute to increase sectoral growth as migrants in Indonesia often open their own business and eventually become more prosperous than non-migrants. However, as in all regression models (Step 1-3), I have controlled local population at the initial year, which seems to be closely related with the number of migrants, though not using the ideal measure such as share of migrants in total population. My regressions show that initial population does not significantly contribute to the district economy.

In short, I find evidence that resource dependence spurs growth in post-decentralisation Indonesia working in small part through improving institutional quality and mostly in ways not identified. Resource dependence seems as beneficial for weaker institution districts as it is for stronger ones.

3.6 Appendices

Appendix 3.1. Definition of Variables and Data Sources

Variable	Definition	Source
Δ Real GRDP per capita (in logs)	The natural logarithm of difference of real GRDP per capita, formulated as: $\Delta\text{GRDP per capita} = ln\,(\frac{GRDP_{percapita,2015}}{GRDP_{percapita,2007}})$	INDO DAPOER World Bank (can be downloaded here: https://datacatalog.worldbank.org/dataset/indonesia-database-policy-and-economic-research) The Indonesian National Statistical Agency (BPS) (see https://www.bps.go.id/)
Earthquake	The number of earthquake events at the district level	Indonesian National Board for Disaster Management (BNPB). Can be accessed online here: http://dibi.bnpb.go.id/dibi/
ΔLabour force partic.rate	The change in labour force participation rate between 2015 and 2007	INDO DAPOER World Bank, BPS
GRDP per capita, 2006 (in logs)	Natural logarithm of initial GRDP percapita in 2006	INDO DAPOER World Bank, BPS
Population, 2006 (in logs)	Natural logarithm of initial population in 2006	BPS
DURBAN	Dummy urban status (municipalities) = 1 if urban districts, = 0 if non-urban/rural district	Identity of urban district/municipality is taken from the Ministry of Home Affairs, the Republic of Indonesia
DJAVA	Dummy of Java Island = 1 if the districts are located on Java Island, = 0 otherwise	-
ΔMining Dependence	The difference in mining dependence between 2015 and 2007	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔMining Revenue	The difference in mining revenue shares, between 2015 and 2007	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS

Variable	Definition	Source
ΔOilGas Revenue	The difference in oil and gas revenue shares, between 2015 and 2007	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
ΔCoal Revenue	The difference in coal revenue shares, between 2015 and 2007	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
OilGas_binary	Dummy variable, = 1 if at least one major oil or gas field operated there during 1970's, = 0 otherwise.	Ooi Jin Bee (1982)
Coal deposit_binary	Dummy variable, =1 if at least 20% of district is covered by a "first generation" coal agreement contract during the 1970's, = 0 otherwise.	Leeuwen (1994); Friederich & Leeuwen (2017)
OilGas_continuous	The number of major and minor oil and gas fields in the 1970's production period in all Island of Indonesia. Major oil and natural gas fields is weigted by 1, and all minor fields are weighted by 0.25. So, if district A has a 10 minor oil/gas fields location, therefore: $District_A = 10 \times 0.25 = 2.5$	Ooi Jin Bee (1982)
Coal deposit_continous	The share of coal deposit areas (shown by first generation coal agreement contract introduced by Leeuwen (1994, 2017)) of total area of respective district.	Leeuwen (1994); Friederich & Leeuwen (2017)
ΔPublic spending	The difference in public capital spending shares, between 2015 and 2007	Ministry of Finance
ΔNet enrolment ratio	The difference in net enrolment ratio between 2015 and 2007	Ministry of Education and Culture, the Republic of Indonesia
ΔManufact (in 10's of trillions of IDR)	The difference in GRDP of manufacturing sector between 2015 and 2007	INDO DAPOER World Bank, BPS

Variable	Definition	Source
ΔInstitutional Quality	The difference in the result of audit opinion score of each district between 2015 and 2007. The opinion ranges from the worst to the best: cannot give any opinion, here scored as 1, to some degree acceptable = 2; perform well/qualified, but corrections needed = 3; qualified without any exception = 4.	The Audit Board of the Republic of Indonesia (www.bpk.go.id)
InsQual06	The initial institutional quality of district in 2006 based on the audit opinion score.	The Audit Board of the Republic of Indonesia (www.bpk.go.id)
InsQual10	The initial institutional quality of district in 2010 based on score of local governance performance index.	The Ministry of Home Affairs of the Republic of Indonesia. (http://otda.kemendagri.go.id/FormMenu/DaftarEKPPD)

Appendix 3.2. OLS and IV regressions: resource dependence and manufacturing size

VARIABLES	(1) FD1	(1') IV-GMM	(2) FD1	(2') IV-GMM	(3) FD1	(3') IV-GMM	(4) FD1	(4') IV-GMM
ΔMining Dependence	0.081	0.319*						
	(0.053)	(0.184)						
ΔMining Revenue			0.183**	0.255**				
			(0.074)	(0.122)				
ΔOilGas Revenue					0.378***	0.385**		
					(0.119)	(0.167)		
ΔCoal Revenue							-0.595***	-0.710*
							(0.209)	(0.367)
Earthquake	-0.002	0.003	-0.002	0.003	-0.003	0.000	-0.005	-0.005
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
ΔLabour force partic.rate	0.033	0.073*	0.062	0.116**	0.073*	0.105**	0.003	-0.003
	(0.045)	(0.044)	(0.046)	(0.048)	(0.044)	(0.045)	(0.048)	(0.053)
GRDP per capita, 2006 (in logs)	0.062**	0.032*	0.066**	0.026	0.083***	0.071**	0.076***	0.077**
	(0.027)	(0.018)	(0.027)	(0.017)	(0.029)	(0.028)	(0.028)	(0.034)
Population, 2006 (in logs)	0.045***	0.040***	0.047***	0.040***	0.048***	0.044***	0.042***	0.041***
	(0.010)	(0.008)	(0.010)	(0.008)	(0.010)	(0.008)	(0.010)	(0.010)
DURBAN	-0.001	0.019	-0.003	0.014	-0.013	0.005	-0.016	-0.020
	(0.019)	(0.016)	(0.019)	(0.014)	(0.020)	(0.016)	(0.021)	(0.022)
DJAVA	0.056***	0.054**	0.045**	0.019	0.034**	0.020	0.043**	0.040**
	(0.022)	(0.024)	(0.018)	(0.016)	(0.016)	(0.017)	(0.018)	(0.017)
Constant	-0.482***	-0.352***	-0.503***	-0.315***	-0.562***	-0.502***	-0.496***	-0.494***
	(0.136)	(0.091)	(0.136)	(0.082)	(0.142)	(0.127)	(0.131)	(0.140)
Observations	390	390	390	390	390	390	390	390
R-squared	0.200	0.122	0.204	0.153	0.227	0.219	0.219	0.218
Kleibergen F-stat		12.27		9.046		16.08		14.16
Hansen *J* P-val		0.252		0.194		0.240		0.545
Endog P-val		0.0397		0.133		0.208		0.755

Notes: Dependent variable is Δ Manufacturing GRDP. The year difference is 2007 to 2015. Instruments used are districts historical resource abundance in the 1970's and the 1980's (binary form) and the change in physical resource production for oil, natural gas, and coal minerals. Standard errors are in parentheses. *, **, ***refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 3.3. OLS and IV regressions: resource dependence and net enrolment ratio

VARIABLES	(1) FD	(1') IV-GMM	(2) FD	(2') IV-GMM	(3) FD	(3') IV-GMM	(4) FD	(4') IV-GMM
ΔMining Dependence	0.119***	0.381***						
	(0.044)	(0.119)						
ΔMining Revenue			0.198***	0.282***				
			(0.060)	(0.099)				
ΔOilGas Revenue					0.190***	0.302***		
					(0.064)	(0.106)		
ΔCoal Revenue							0.102	0.206
							(0.137)	(0.229)
Earthquake	-0.011**	-0.010*	-0.011**	-0.011**	-0.012**	-0.012**	-0.011**	-0.011**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ΔLabour force partic.rate	-0.080	-0.089*	-0.049	-0.040	-0.060	-0.052	-0.075	-0.069
	(0.051)	(0.050)	(0.053)	(0.054)	(0.052)	(0.053)	(0.054)	(0.054)
GRDP per capita, 2006 (in logs)	-0.031***	-0.022**	-0.028***	-0.027***	-0.024**	-0.017	-0.038***	-0.041***
	(0.009)	(0.011)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)	(0.012)
Population, 2006 (in logs)	0.001	-0.000	0.002	0.002	0.001	0.001	0.000	0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
DURBAN	-0.016	-0.016	-0.018	-0.018	-0.023	-0.026	-0.015	-0.012
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.018)
DJAVA	-0.008	0.016	-0.023	-0.022	-0.025	-0.028*	-0.015	-0.013
	(0.015)	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Constant	0.298***	0.256***	0.283***	0.282***	0.275***	0.255***	0.329***	0.335***
	(0.055)	(0.061)	(0.056)	(0.059)	(0.057)	(0.063)	(0.055)	(0.055)
Observations	390	390	390	390	390	390	390	390
R-squared	0.083	-0.002	0.082	0.079	0.079	0.074	0.067	0.065
Kleibergen F-stat		12.27		9.046		16.08		14.16
Hansen *J* P-val		0.377		0.376		0.278		0.794
Endog P-val		0.0529		0.507		0.304		0.598

Notes: Dependent variable is Δ Net Enrolment Ratio, High School.The year difference is 2007 to 2015. Instruments used are districts historical resource abundance in the 1970's and the 1980's (binary form) and the change in physical resource production for oil, natural gas, and coal minerals. Standard errors are in parentheses. *, **, ***refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 3.4. OLS and IV regressions: resource dependence and institutional quality

VARIABLES	(1) FD	(1') IV-GMM	(2) FD	(2') IV-GMM	(3) FD	(3') IV-GMM	(4) FD	(4') IV-GMM
ΔMining Dependence	0.700*	2.499***						
	(0.404)	(0.889)						
ΔMining Revenue			1.583***	3.208***				
			(0.585)	(0.629)				
ΔOilGas Revenue					0.986	2.195**		
					(0.698)	(1.003)		
ΔCoal Revenue							2.667***	5.051***
							(0.967)	(1.936)
Earthquake	-0.00480	-0.0118	-0.00162	0.00203	-0.00729	-0.0144	0.00474	0.0176
	(0.0471)	(0.0470)	(0.0481)	(0.0474)	(0.0478)	(0.0473)	(0.0481)	(0.0484)
ΔLabour force partic.rate	0.284	0.326	0.532	0.966**	0.389	0.592	0.421	0.556
	(0.491)	(0.479)	(0.501)	(0.481)	(0.498)	(0.495)	(0.494)	(0.492)
GRDP per capita, 2006 (in logs)	0.317***	0.392***	0.349***	0.429***	0.355***	0.436***	0.221**	0.166*
	(0.0794)	(0.0829)	(0.0775)	(0.0760)	(0.0876)	(0.0986)	(0.0869)	(0.0956)
Population, 2006 (in logs)	-0.130*	-0.123*	-0.115*	-0.106	-0.127*	-0.123*	-0.123*	-0.122*
	(0.0677)	(0.0674)	(0.0686)	(0.0681)	(0.0681)	(0.0680)	(0.0684)	(0.0676)
DURBAN	-0.475***	-0.481***	-0.489***	-0.518***	-0.510***	-0.562***	-0.419***	-0.360**
	(0.137)	(0.135)	(0.136)	(0.133)	(0.138)	(0.137)	(0.143)	(0.147)
DJAVA	0.340***	0.487***	0.239*	0.224*	0.246*	0.204	0.321**	0.379***
	(0.129)	(0.138)	(0.129)	(0.128)	(0.132)	(0.135)	(0.128)	(0.127)
Constant	0.640	0.250	0.466	0.0990	0.538	0.249	0.930*	1.042**
	(0.515)	(0.548)	(0.521)	(0.521)	(0.533)	(0.570)	(0.507)	(0.509)
Kleibergen		12.266		9.046		16.081		14.164
Hansen		0.0665		0.0615		0.0982		0.0730
Endog		0.1681		0.0726		0.2110		0.1954
Observations	390	390	390	390	390	390	390	390
R-squared	0.064	0.013	0.070	0.055	0.061	0.053	0.066	0.058

Notes: Dependent variable is Δ Institutional Quality.The year difference is 2007 to 2015. Instruments used are districts historical resource abundance in the 1970's and the 1980's (binary form) and the change in physical resource production for oil, natural gas, and coal minerals. Standard errors are in parentheses. *, **, ***refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 3.5. OLS and IV regressions: resource dependence and public spending on capital

VARIABLES	(1) FD	(1') IV-GMM	(2) FD	(2') IV-GMM	(3) FD	(3') IV-GMM	(4) FD	(4') IV-GMM
ΔMining Dependence	0.059	-0.066						
	(0.042)	(0.140)						
ΔMining Revenue			0.057	0.001				
			(0.082)	(0.128)				
ΔOilGas Revenue					-0.069	0.015		
					(0.085)	(0.149)		
ΔCoal Revenue							0.453**	0.343
							(0.182)	(0.283)
Earthquake	0.004	0.004	0.004	0.004	0.004	0.004	0.005	0.005
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
ΔLabour force partic.rate	0.005	0.007	0.014	0.005	-0.002	0.000	0.028	0.035
	(0.043)	(0.042)	(0.043)	(0.042)	(0.044)	(0.041)	(0.044)	(0.045)
GRDP per capita, 2006 (in logs)	0.024**	0.015	0.025**	0.017*	0.018*	0.021*	0.010	0.016
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)	(0.012)
Population, 2006 (in logs)	0.012*	0.013**	0.012*	0.013**	0.011*	0.011*	0.013**	0.015**
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
DURBAN	-0.012	-0.006	-0.013	-0.005	-0.011	-0.011	-0.002	-0.007
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)
DJAVA	-0.007	-0.019	-0.014	-0.013	-0.009	-0.012	-0.006	-0.011
	(0.012)	(0.016)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Constant	-0.163***	-0.130**	-0.163***	-0.140***	-0.133**	-0.143***	-0.127**	-0.152***
	(0.056)	(0.052)	(0.054)	(0.051)	(0.053)	(0.054)	(0.057)	(0.056)
Observations	390	390	390	390	390	390	390	390
R-squared	0.038	0.009	0.034	0.031	0.035	0.031	0.066	0.063
Kleibergen F-stat		12.27		9.046		16.08		14.16
Hansen *J* P-val		0.127		0.108		0.494		0.0291
Endog P-val		0.440		0.725		0.476		0.767

Notes: Dependent variable is Δ public capital spending shares. The year difference is 2007 to 2015. Instruments used are districts historical resource abundance in the 1970's and the 1980's (binary form) and the change in physical resource production for oil, natural gas, and coal minerals. Standard errors are in parentheses. *, **, ***refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 3.6. Results for IV Ordered Probit

Table 4.B. IV Ordered Probit results (1)

```
Fitting full model.

Mixed-process regression                         Number of obs    =        390
                                                 LR chi2(18)      =     104.72
Log likelihood =  21.643745                      Prob > chi2      =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
insqual						
Dmindep	2.397385	2.210105	1.08	0.278	-1.934342	6.729112
Earthquake	.0103826	.072201	0.14	0.886	-.1311288	.1518939
Dlabforce	.3123822	.6050338	0.52	0.606	-.8734622	1.498227
lgdp_percap06	.4899879	.1291693	3.79	0.000	.2368207	.7431552
lpop_06	-.1192947	.0881295	-1.35	0.176	-.2920252	.0534359
DURBAN	-.443077	.1842651	-2.40	0.016	-.8042299	-.081924
DJAVA	.7908863	.233389	3.39	0.001	.3334522	1.24832
Dmindep						
Earthquake	-.0012076	.0069572	-0.17	0.862	-.0148436	.0124283
Dlabforce	.0354972	.0572194	0.62	0.535	-.0766508	.1476452
lgdp_percap06	-.0163473	.0115238	-1.42	0.156	-.0389336	.0062389
lpop_06	-.0034159	.0079672	-0.43	0.668	-.0190314	.0121995
DURBAN	-.0188399	.0174848	-1.08	0.281	-.0531094	.0154297
DJAVA	-.0820586	.0176259	-4.66	0.000	-.1166048	-.0475123
oilgasabundance	-.0438286	.0120591	-3.63	0.000	-.0674641	-.0201931
coalabundance	.0007927	.0004853	1.63	0.102	-.0001585	.0017438
d_oilproduction	7.02e-06	2.07e-06	3.39	0.001	2.96e-06	.0000111
d_gasproduction	4.22e-07	2.05e-07	2.05	0.040	1.93e-08	8.25e-07
d_coalproduction	.000012	.0000151	0.79	0.428	-.0000177	.0000417
_cons	.126777	.0635278	2.00	0.046	.0022647	.2512893
/cut_1_1	-.6676711	.8583157	-0.78	0.437	-2.349939	1.014597
/cut_1_2	.7528505	.7927874	0.95	0.342	-.8009842	2.306685
/lnsig_2	-2.079755	.0358253	-58.05	0.000	-2.149972	-2.009539
/atanhrho_12	-.223616	.3088928	-0.72	0.469	-.8290347	.3818027
sig_2	.1249608	.0044768			.1164875	.1340504
rho_12	-.2199618	.2939476			-.6799574	.364272

Table 4.C. IV Ordered Probit results (2)

```
Fitting constant-only model for LR test of overall model fit.

Fitting full model.

Mixed-process regression                          Number of obs   =        390
                                                  LR chi2(18)     =     239.64
Log likelihood =  280.65654                       Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
insqual						
Dminrev	2.601611	1.905236	1.37	0.172	-1.132583	6.335804
Earthquake	.0104012	.0727478	0.14	0.886	-.1321818	.1529843
Dlabforce	.7608558	.6957397	1.09	0.274	-.602769	2.124481
lgdp_percap06	.5401938	.1433795	3.77	0.000	.2591751	.8212124
lpop_06	-.1103272	.0892259	-1.24	0.216	-.2852067	.0645523
DURBAN	-.5150217	.1837818	-2.80	0.005	-.8752274	-.154816
DJAVA	.5517758	.20153	2.74	0.006	.1567843	.9467673
Dminrev						
Earthquake	-.0023459	.0035897	-0.65	0.513	-.0093815	.0046897
Dlabforce	-.1205604	.0295237	-4.08	0.000	-.1784257	-.0626951
lgdp_percap06	-.0203369	.00588	-3.46	0.001	-.0318615	-.0088123
lpop_06	-.0075759	.0041022	-1.85	0.065	-.0156161	.0004643
DURBAN	-.0016027	.0090116	-0.18	0.859	-.0192652	.0160597
DJAVA	.0209335	.0090777	2.31	0.021	.0031414	.0387255
oilgasabundance	-.0507079	.0058776	-8.63	0.000	-.0622279	-.039188
coalabundance	.0009079	.0002516	3.61	0.000	.0004148	.0014011
d_oilproduction	7.62e-06	1.05e-06	7.24	0.000	5.56e-06	9.68e-06
d_gasproduction	3.28e-07	1.04e-07	3.15	0.002	1.24e-07	5.33e-07
d_coalproduction	.0000289	7.74e-06	3.74	0.000	.0000137	.0000441
_cons	.1190843	.0324601	3.67	0.000	.0554636	.1827049
/cut_1_1	-.5955566	.7846803	-0.76	0.448	-2.133502	.9423887
/cut_1_2	.8632438	.7715399	1.12	0.263	-.6489466	2.375434
/lnsig_2	-2.741195	.0358065	-76.56	0.000	-2.811374	-2.671015
/atanhrho_12	-.0531601	.1447518	-0.37	0.713	-.3368683	.2305482
sig_2	.0644932	.0023093			.0601223	.069182
rho_12	-.05311	.1443435			-.3246787	.2265485

Table 4.D. IV Ordered Probit results (3)

```
Fitting constant-only model for LR test of overall model fit.

Fitting full model.

Mixed-process regression                          Number of obs   =        390
                                                  LR chi2(16)     =     291.48
Log likelihood =   290.3589                       Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
insqual						
Doilgasrev	.6132104	2.147491	0.29	0.775	-3.595794	4.822215
Earthquake	.0054346	.0725938	0.07	0.940	-.1368467	.1477159
Dlabforce	.4076728	.6556223	0.62	0.534	-.8773232	1.692669
lgdp_percap06	.4646745	.1763289	2.64	0.008	.1190763	.8102728
lpop_06	-.1340765	.0870751	-1.54	0.124	-.3047405	.0365875
DURBAN	-.4988813	.1922271	-2.60	0.009	-.8756396	-.1221231
DJAVA	.5995634	.2086618	2.87	0.004	.1905938	1.008533
Doilgasrev						
Earthquake	.0004046	.0034697	0.12	0.907	-.0063959	.0072051
Dlabforce	-.0737529	.0284768	-2.59	0.010	-.1295665	-.0179394
lgdp_percap06	-.039004	.0052649	-7.41	0.000	-.049323	-.0286851
lpop_06	-.0017773	.0039496	-0.45	0.653	-.0095184	.0059639
DURBAN	.0154619	.0085464	1.81	0.070	-.0012887	.0322125
DJAVA	.0271339	.0086761	3.13	0.002	.0101291	.0441387
oilgasabundance	-.0475285	.0054851	-8.67	0.000	-.058279	-.036778
d_oilproduction	6.58e-06	1.03e-06	6.36	0.000	4.55e-06	8.60e-06
d_gasproduction	4.30e-07	9.71e-08	4.43	0.000	2.40e-07	6.20e-07
_cons	.1381888	.030726	4.50	0.000	.077967	.1984105
/cut_1_1	-1.011128	.8264118	-1.22	0.221	-2.630865	.6086095
/cut_1_2	.4408273	.8231766	0.54	0.592	-1.172569	2.054224
/lnsig_2	-2.769859	.0358062	-77.36	0.000	-2.840038	-2.69968
/atanhrho_12	.0523457	.1559391	0.34	0.737	-.2532893	.3579808
sig_2	.0626708	.002244			.0584235	.067227
rho_12	.052298	.1555126			-.2480082	.3434342

Table 4.E. IV Ordered Probit results (4)

```
Fitting constant-only model for LR test of overall model fit.

Fitting full model.

Mixed-process regression                              Number of obs   =        390
                                                      LR chi2(15)     =     254.65
Log likelihood =  529.69383                           Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
insqual						
Dcoalrev	12.00295	4.748857	2.53	0.011	2.695365	21.31054
Earthquake	.0476252	.073787	0.65	0.519	-.0969946	.192245
Dlabforce	.802738	.6370638	1.26	0.208	-.4458841	2.05136
lgdp_percap06	.2071915	.1495523	1.39	0.166	-.0859255	.5003086
lpop_06	-.0832725	.0884121	-0.94	0.346	-.2565569	.090012
DURBAN	-.2800355	.2002686	-1.40	0.162	-.6725546	.1124837
DJAVA	.6974851	.1905797	3.66	0.000	.3239558	1.071015
Dcoalrev						
Earthquake	-.0028144	.0019016	-1.48	0.139	-.0065414	.0009127
Dlabforce	-.0536498	.0155017	-3.46	0.001	-.0840326	-.0232671
lgdp_percap06	.0135194	.0028925	4.67	0.000	.0078502	.0191885
lpop_06	-.0056004	.0021503	-2.60	0.009	-.0098148	-.0013859
DURBAN	-.0128514	.0047052	-2.73	0.006	-.0220735	-.0036293
DJAVA	-.0055631	.0047717	-1.17	0.244	-.0149155	.0037894
coalabundance	.0007928	.0001262	6.28	0.000	.0005455	.0010402
d_coalproduction	.0000391	3.92e-06	9.98	0.000	.0000314	.0000468
_cons	-.0016231	.0163555	-0.10	0.921	-.0336794	.0304332
/cut_1_1	-1.393666	.6547879	-2.13	0.033	-2.677026	-.1103049
/cut_1_2	.0329332	.6470993	0.05	0.959	-1.235358	1.301224
/lnsig_2	-3.376031	.0358058	-94.29	0.000	-3.44621	-3.305853
/atanhrho_12	-.2671625	.1729958	-1.54	0.123	-.6062282	.0719031
sig_2	.0341828	.0012239			.0318662	.0366679
rho_12	-.2609826	.1612128			-.5414666	.0717794

Appendix 3.7. Information of several scatterplots on several variables

Fig 3. Scatterplot of average share of oil and gas revenues in total local government budget on net enrolment ratio in high school, with regression line, between 2007-2015

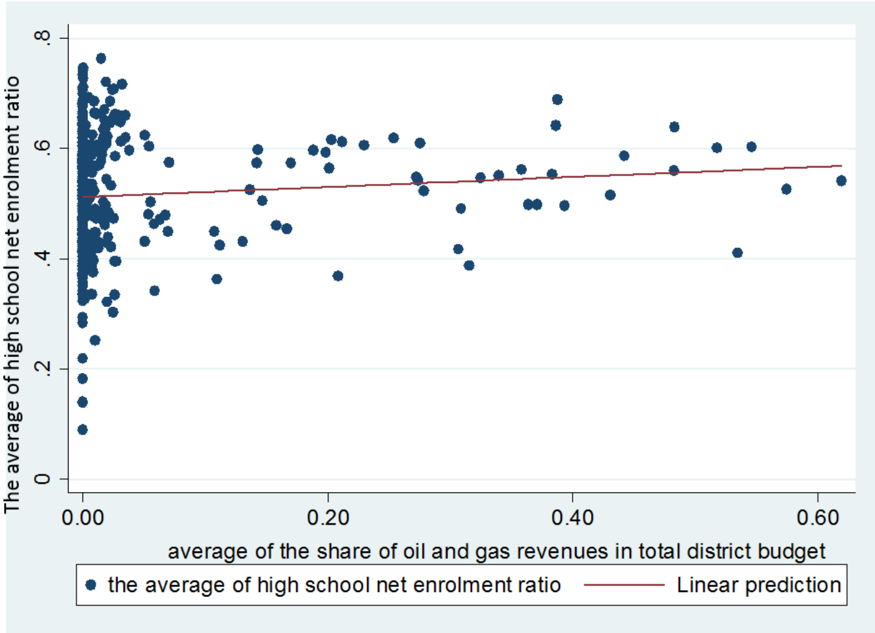


Fig 4. Scatterplot of average institutional quality (auditor opinion score) on district's growth in GRDP per capita, with regression line, between 2007-2015

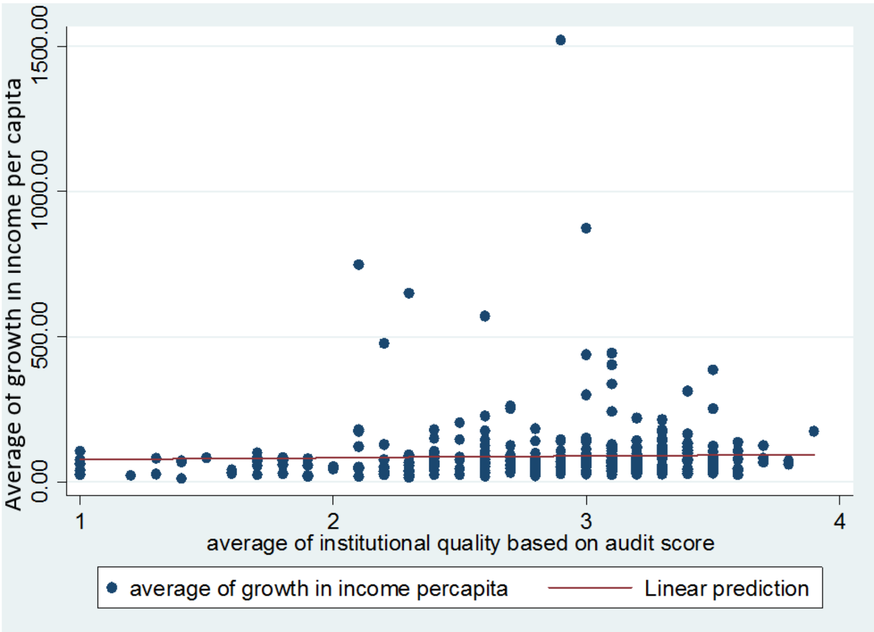
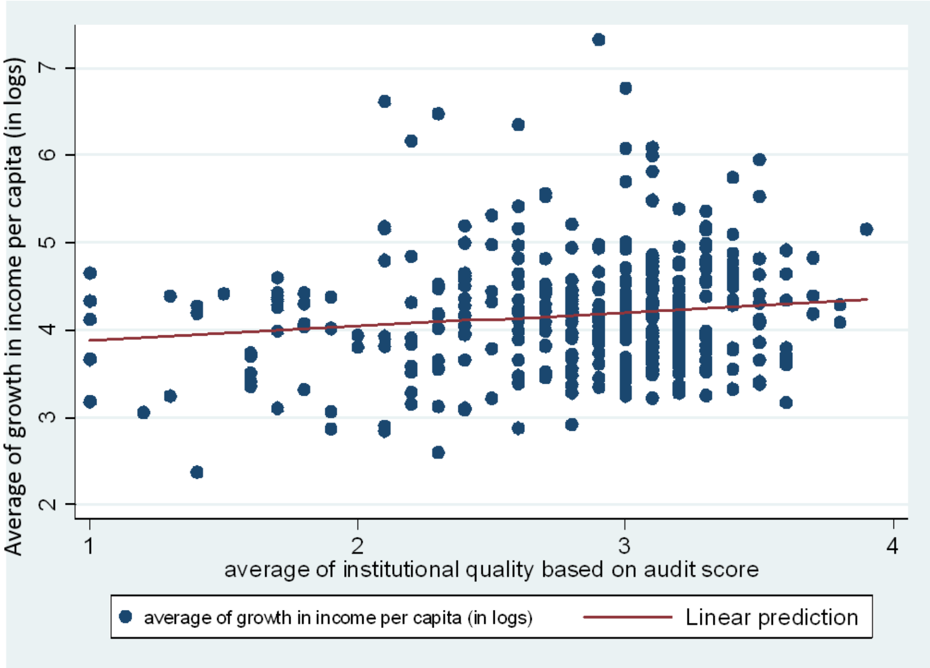


Fig 5. Scatterplot of average of institutional quality (auditor opinion score) on district's GRDP per capita (in logs), with regression line, between 2007-2015



4 CHAPTER FOUR

The Spatial Effects of Resource Dependence in Indonesia

4.1 Introduction

4.1.1 Background

The positive impact of natural resources on income growth has been found in a number of studies both cross-country (e.g. Brunnschweiler (2008); Brunnscheweiler and Bulte (2008); Ouoba (2016); Bjorvatn, Farzanegan and Schneider (2012)) and within-country (e.g. Weber (2012); Libman (2013); Fleming & Measham (2015); Cust and Rusli (2016)). A recent investigation by Hilmawan and Clark (2018) also finds evidence of a “resource blessing” at the district level for Indonesia. They find using district first differences that a greater dependence on resources positively affects income per capita, whether dependence is measured as the proportion of mining in district GRDP or as a fraction of oil revenues in district government budgets.

Recent resource curse/blessing studies have also attempted to investigate the effects of resource dependence beyond per capita income on other wellbeing and development indicators. Some have looked at the effects of resources-based activities on poverty rates (e.g. Zhang, Xing, Fan & Luo, 2008; Weber, 2012; Partridge, Betz & Lobao, 2013; Bhattacharya and Resosudarmo, 2015), education/human capital (Weber, 2014; Douglas and Walker, 2016; Edwards, 2016a; Carpenter, Anderson and Dudensing, 2019), or health outcomes (Edwards, 2016a; Cotet and Tsui, 2013; El Anshasy and Katsaiti, 2015). However, most existing income studies, and all broader effect studies of which I am aware, have focused only on the own country/district effects of resources, i.e. the impact of resources in region *i* on outcomes of interest in the same region.

Yet resource effect scholars have increasingly shifted to within-country studies, testing the localised effect of resource dependence while holding constant national characteristics that affect growth (e.g. van der Ploeg, 2011; Fleming, Measham & Paredes, 2015; Douglas & Walker, 2016). As the unit of observation for resource dependence effects has grown finer, concerns have been raised about the neglect of geographical spillovers. Although geographical variables have been used in some resource growth studies, they have been limited to coarse binary measures such as whether the geographic unit is landlocked, or tropical (e.g. van der Ploeg and Poelhekke, 2009; Daniele, 2011), rather than addressing spatial dependence more generally. In contrast, other areas of applied economic research have long considered spatial-related factors, inspired by methods developed in regional science and urban economics, where economic activities and geographical positions have long been recognized as mutually dependent. This dependence is widely known as Tobler's Law, after Tobler (1970, p.236) who proposed the "first law of geography" that *"everything is related to everything else, but near things are more related than distant things."*

Is having more resource dependent neighbours beneficial or harmful to a host region's income? This question has been posed against a backdrop of wider debate as to whether natural resources help or hurt a country's economic growth and development. Yet spatial effects could have a bearing on this broader debate. For example, suppose that district *i* is a resource-poor region with low income per capita but geographically surrounded by oil-rich districts as its nearest neighbours. During an oil boom, potential labour in district *i* could migrate to its neighbours, lowering economic production in *i* and reducing growth. Conversely, the same home district's economy could benefit if the mining sector in adjacent areas produces spillovers to district *i*, such as higher derived demand for supporting goods or services. The last possibility is that no spatial spillovers are produced, such as when both home and neighbour districts simply compete, or lack infrastructure that connects them. This last possibility, if supported, might suggest that mining or oil and gas-based extraction has low productive linkages with other sectors in proximity.

Investigations which test for spatial spillovers have been used in economic studies of crime (Öcal and Yildirim, 2010; Torres-Preciado, Gaytán & Zermeño, 2017), foreign direct investment (Madariaga & Poncet, 2007), institutions (Bosker and Garretsen 2009; Hall and Ahmad, 2012; Ganau, 2017), and in economic growth, such as the effects of regional instability on home area economic growth (Chua & Ades (1993); Ades & Chua (1997); Murdoch & Sandler, 2016), or the effect of neighbouring countries on home country growth more generally (Easterly and Levine, 1997; Gibson, 2007; Abderrezak, 2005).

In contrast, studies of resource effects have been slower to incorporate spatial effects. The few studies that do are focussed on developed countries, primarily the United States (e.g. Weber, 2014; Lee, 2015; Weinstein, et al. 2018), or Australia (Fleming et al. 2015). I am not aware of any resource effect studies in developing countries that have examined spatial spillovers in within-country studies. A working paper by Carmignani (2014) is the first that includes spillovers in a sample that includes developing countries, but is a between-country study. Since developing countries are generally more reliant on commodity-based sectors, and have poorer transportation networks, the issue of resource effect spillovers seems likely to play a greater role there. This makes a study of a large resource-based developing economy such as Indonesia especially relevant.

For Indonesia in particular, district level decentralisation was fully implemented in 2005, including local elections of district governments. This has meant that each district has had authority to manage its local budget. As a result, resource-rich districts tend to get higher revenues from this policy. This may improve the quality of governance of such districts, which might raise own per capita incomes or affect their key development indicators, and possibly create spillover effects to nearby districts. For example, suppose one district has had its GRDP historically dominated by oil extraction. Does this reliance benefit the district itself? Does it generate major external benefits (or costs) to nearby districts?

Indonesia provides an excellent opportunity for both within-country analysis of resource effects, but also spatial analysis. Indonesia is grouped in five big islands stretching from west to east, comprising more than 500 districts across the Indonesian archipelago as of 2017. Thus, the inter-district interactions among "nearest" neighbour districts may be intense in the big islands but limited for smaller or isolated island districts.[83] Second, as natural resource endowments are distributed unevenly across islands, they provide a source of exogenous variation regarding where resources extraction activities take place. This is true for onshore and offshore wells of oil or gas drilling activities, or the sites of mining operations. Abundance is a necessary condition for extraction and dependence.

From the view of my wider dissertation, this chapter tries to finalise investigations of the impact of local resource dependence on income in Indonesia by also including spatial spillovers of resource dependence, but also to broaden the outcomes of interest beyond per capita income to other development indicators. Recall that the first chapter measured the

[83] The Indonesia administrative hierarchy starts from Province, then Sub-Province or District, Sub-District (or *Kecamatan*) and Village (*Kelurahan*/*Desa*). The latter two administrative units are regularly reported by the Indonesia Statistics Office (BPS) but the variables provided are limited and not available for wide time intervals. See an illustrative map of Indonesia in Appendix 4.3., Figure A1 to see how the potential for interactions between districts might vary.

direct effect of resource dependence on income and found it positive, while the second chapter has sought to identify some potential causal mechanisms for these beneficial effects. This chapter will identify whether these beneficial effects of own district resource dependence on own district outcomes are augmented or reduced when spatial spillovers from adjacent districts are considered.

This study thus makes three contributions. First, it fills the gap in the resource effects literature regarding spatial spillover effects for a developing country. Second, it investigates the effects of resource dependence on key development indicators for Indonesia, including poverty, education and health outcomes. This would be the first within country resource effect study of Indonesia to do so. Finally, methodologically, by trying three different spatial weighting specifications to identify 'nearest neighbours', it contributes to the discussion of whether choice of neighbour measure matters. Most spatial effect studies use a single spatial weighting method, yet different studies use different methods (Carmignani (2014); Weber (2014); Bosker & Garretsen (2009)).

The remainder of this chapter is organised as follows. Section 4.2 reviews recent within-country studies of the effects of resource dependence on income, emphasizing those that have included spatial effects. It also reviews those resource studies that have examined broader development outcomes. Section 4.3 describes the data and estimation strategy used in my regression analysis. Section 4.4 provides initial descriptive analysis and my main regression results for each outcome of interest. Section 4.5 will then discuss my main findings and Section 4.6. concludes.

4.2 Literature Review

In this section, I review studies focusing not only the effects of natural resources on income per capita or economic growth in general, but also on social development measures. I will select empirical studies that use cross-country data comparison in a specific continent, but since more recent works have emphasized within-country analysis, the latter will be prioritized.

In most studies reviewed, natural resources are measured using "dependence" or "extraction" despite criticisms of the potential endogeneity of such measures (i.e. poor countries might be more reliant on mining due to low savings and investments in manufacturing). Dependence rather than abundance measures are used, however, because it is harder to posit that endowments trapped in the ground untouched would affect a country's economic or development outcomes (Marchand and Weber (2018), Douglas and Walker (2016)).[84] Nonetheless, recent within-country studies have shifted to exploit available abundance information related to the numbers of oil or/and gas wells, or drilling activities. Unfortunately, these studies consider only developed economies such as the United States (see detailed discussion, for example Marchand and Weber (2018)).[85] Another reason for using resource dependence measures is that in developing countries, resource abundance data such as oil reserves or locations of drilled wells are often not available over time, or not publicly available.

Below, I will focus on studies of the effects of resource dependence/extraction on income, and on variables associated with other development outcomes. I will then focus on the limited number of resource effect studies that have controlled for spatial effects.

4.2.1 Resource Dependence Effects on Development Outcomes

4.2.1.1 Effects on Income

A cross-country study by Ouba (2016) examines the effect of resource dependence, measured as a share of resource rents in total GDP, on income. Ouba overcomes the endogenous nature of his dependence measure by using instrumental variables. Focusing on a sample of resource-rich countries in the period 1985-2010 (in averaged five year intervals), and controlling for human capital, institutional quality, and foreign direct investment, Ouba finds that resource rents positively affect income per capita using either IV-2SLS or Driscoll-Kraay (D-K) techniques. He uses the instruments of trade openness and the presidential system. For other examples of cross-country studies, see the review paper by Bjorvatn, et al. (2012).

Studies that have looked at resource effects on income have recently shifted to exploit within-country variations, but perhaps owing to issues of data availability, the majority of

[84] By default, resource dependence is defined as a flow derived from natural resource endowments (e.g. oil, gas, or coal), so often as a share of GDP or percentage of government revenues or share of mining employment in total employment (see for example the within-country studies of James and Aadland (2011); James and James (2011); Weber (2012); and Betz et al. (2015)), or the between country studies of Edwards (2016a), Ouoba (2016), or Bjorvatn, Farzanegan, and Schneider (2012).

[85] Alternatively, resource effect scholars use resource abundance measures. These are estimates of resource stocks, such as proven reserves. Although one can argue that such endowments would not affect a country's economy while trapped in the ground, some researchers use abundance to measure an exogenuous natural resource effect, or have used abudance as an instrument only (e.g. Brunscheweiler and Bulte, 2008).

these have been done in developed states (e.g. Hajkowich, Heyenga and Moffat (2011) and Fleming and Measham (2015) for Australia, Boyce and Emery (2011), James & Aadland (2011), Weber (2012, 2014), Lee (2015) and Douglas and Walker (2016) for the United States, and Libman (2013) for Russia). However, there are also a few within-country studies for developing countries, such as Aragón and Rud (2013) for Peru, Cust and Rusli (2016) for Indonesia, and more recently Hota and Behera (2019) for India.

To illustrate, James and Aadland (2011) investigate whether United States counties' dependence on natural resources, measured as a share of mining, agriculture, forestry and fishing earnings in 1980, affects annual growth of per capita personal income between 1980 and 1995 for 3,092 counties. They perform two-stage generalized least squares (GLS) and control for initial income per capita, population, poverty and education in 1980. James and Aadland find that resource dependence lowered subsequent growth. The results remain robust even when the period is separated using a 5, 10, or 15-year interval. In contrast, Libman (2013) investigates the effect of oil and gas extraction, measured by the share of oil and gas value in total gross regional product (GRP), on the growth of the GRP of 72 Russian regions, averaged over the period 2000- 2006. Using cross-section regression for the sampled regions, he finds a positive effect of oil and gas dependence on growth under an OLS estimator, but the positive effect is no longer significant once regional fixed-effects are included.

In a more locally focussed study, Fleming and Measham (2015) evaluate the local economic impacts of new coal seam gas (CSG) extraction in southern Queensland, Australia. They evaluate the impact of this extraction on several indicators of income and employment between 2001 and 2011. The first OLS estimates reveal that the presence of CSG-related wells (a binary variable) has a positive and significant effect on growth in median per capita or family income. They control for initial (2001) population density, median per capita income, and education. Agglomeration effects caused by the large Brisbane economy are also controlled by including the distance (in km) between the respective local area and Brisbane.

While not spatial, Fleming and Measham's analysis also demonstrates how growth in mining employment can spill over to growth in non-mining employment. Contrary to a 'Dutch disease' prediction of crowding out, where resource booms are predicted to hurt tradable sectors such as manufacturing exports, Fleming and Measham find a CSG boom leads to growth in some other local goods sectors. In particular, by applying 2SLS and using the location of CSG-wells as an instrumental variable, the authors find that mining-related job growth had positive spillovers in the construction and professional services sectors, but negative spillovers for agriculture, and no net effect on the manufacturing sector.

Still in Australia, Hajkowich, et al. (2011) test the effect of mineral production based on gross value on indicators reflecting regional quality of life, using local government boundaries. Their study reveals no evidence of negative effects on the outcome measures. By using cross-correlation analysis, for instance, Hajkowich et al. find that the gross value of minerals production has strong positive and statistically significant (at 1 % level) correlation with household income.

In another within country study, Weber (2014) examines the effects of the change in natural gas production (in billions of cubic feet) on the change in total employment and earnings per job in the south-central United States, using a difference in difference approach: a change from 2000 to 2010 minus the change from 1995 to 2000. Weber uses 362 non-metropolitan counties in Arkansas, Lousiana, Oklahoma, and Texas, and by using a GMM estimator finds that natural gas development is positively correlated with both outcome measures. Recognizing that potential endogeneity of gas production may occur, Weber's study uses location of unconventional gas reservoirs over the investigated counties as an instrument. Another within-country study in the United States by Douglas and Walker (2016) concentrates on the more homogenous counties of the Appalachian region where coal mining activities have dominated the overall economy. Douglas and Walker (2016) find that coal mining dependence, measured as the fraction of resource revenue in total personal income, adversely affects growth of per capita personal income over the period 1970-2010 (in annualized 10-year intervals), regardless of whether analysis is conducted with instruments using GMM-Fixed Effects or without instruments based on pooled OLS.

Finally, a recent study by Hota and Behera (2019) concentrates on the effects of mining extraction on development indicators including income across 30 districts in the state of Odisha, India. Hota and Behera focus on Odisha as the largest mineral producing state in India. They find that mining has been a dominant contributor to local government revenues, which they argue has caused different patterns of growth performance among states. To more formally examine this conjecture, Hota and Behera perform a simple ANOVA test, where mining-reliant districts are coded 1 and 0 otherwise. As expected, the results show that mining-based districts have a greater income per capita than their counterparts, and mining's contribution is statistically significant.

4.2.1.2 Effects on Poverty

While most resource researchers have tested the effect of natural resource dependence on growth in income per capita, a smaller number have tried to also test the impact of resources on broader development indicators. For example, do positive associations found between mining or oil dependence and income per capita also result in positive effects on reducing poverty rates and raising living standards?

In line with the belief that a reliance on oil or mining attenuates economic growth, Auty (1994) has argued that resource dependent countries tend to suffer from low development outcomes, including widespread poverty. Alternatively, according to a more traditional view, a nation endowed with oil and minerals that extracts large revenues from them should have a greater capacity to reduce poverty. Two papers examining this issue find there is evidence of slow but sustained poverty alleviation in resource-reliant nations (Ross, 2003; Stevens, 2003).

Specifically, Ross (2003) discusses potential links between mineral extraction and poverty and notes that economic theories have conflicting views with respect to this relationship. On the one hand, nations that are largely reliant on natural resources have often experienced lower growth performance, which could increase poverty rates. On the other hand, resource wealth tends to offer “instant” sources of income linked with an increase in government revenues, enabling local governments to provide transfer programmes that are pro-poor or invest in public goods such as education or health that benefit the poor.

Ross also provides some arguments on why mineral wealth possibly raises poverty. First, Ross argues that linkages between mining and non-mining sectors are relatively weak, which leads to less labour being demanded. Additionally, the mineral sector is particularly vulnerable to external shocks in world commodity prices. Countries that are economically reliant on natural resources are thus more likely to be affected by negative world price shocks, particularly the poor households in those countries. Third, although mining extraction may provide greater economic rents for governments, that income may be disproportionately distributed, potentially raising income inequality and doing little to alleviate poverty. Caselli and Michaels (2013) also emphasize the development implications of increased oil and gas-based production among Brazilian municipalities. They find that while greater oil production may increase government revenues, there is no significant evidence that this raises local household incomes. They attribute this in part to offshore oil activities requiring little local employment.

Moving to resource/poverty studies in developed countries, Black et al. (2005) examine the effects of coal booms and busts at the county level in the 1970's and 1980's in the American states of Pensylvania, West Virginia, Colorado, Ohio and Kentucky. Black et al. find that during a boom, coal counties experienced income increases faster than non-coal counties. Interestingly, poverty rates were alleviated during the boom, but increased to pre-boom levels during the subsequent bust. A study by Weber (2012) also investigates the effect of resource booms at the United States county level, measured using the change in gas production, on poverty rates in Colorado, Texas and Wyoming. Weber finds that with OLS or IV methods, there is no significant evidence poverty rates are affected by boom events. More comprehensively, Patridge, Betz and Lobao (2013) compare all counties in the United States and the Appalachian region in particular for the respective 2000 and 2010 census years. These authors find no strong evidence that poverty rates in 2000 and 2010 were affected by share of employment in oil and gas in their full sample. Nonetheless, when using Appalachian counties only, they find higher oil and gas employment shares are associated with higher rates of poverty in 2010. Using the same regression, however, Patridge, et al. find that coal's share of employment lowered the poverty rate in 2000, though with no significant effect in 2010.

Some within-country studies have also tested for resource effects on poverty rates in the context of Asia. Comparing provinces in China, Zhang, Xing & Fan (2008) investigate the effect of initial resource dependence in 1985, measured as the percentage of resource (coal, oil, and natural gas) production in total GDP, on changes in the incidence of rural poverty from 1988 to 1999. They find initial resource dependence raises the subsequent poverty rate in rural areas, though the authors caution that with only 25 observations used in the poverty specification, the results may not be robust.

Returning to the study for India by Hota and Behera (2019) but now regarding poverty, these authors find that for the specific state of Odisha, the share of mining in district GDP is negatively associated with the percentage in poverty in rural areas. Although this study can shed light on the experience of one emerging nation in Asia, Hota and Behera do not address the potential endogeneity of their resource dependence measure.

Focusing on Indonesia, Bhattacharya and Resosudarmo (2015) use fixed effects analysis at the provincial level between 1977 and 2010, and find growth in mining GRDP per capita (as measured by the difference between real overall GRDP per capita and non-mining GRDP per capita) does not have a significant impact on a poverty head count ratio, though the estimated sign suggests poverty reduction. Bhattacharya and Resosudarmo's measure of mining includes oil, natural gas, and minerals, but they provide no instruments in case it is endogenous. Continuing with Indonesia, now at the district level for the single year of 2009, Edwards (2016a) finds less happy resource effects. Edwards finds that mining dependence significantly raises the incidence of poverty. In particular, a one percent increase in mining share in GRDP raises the percentage of people living under the poverty line by 0.052 percent.

4.2.1.3 Effects on Education

Once again, a few resource effects studies have examined the effects of resource dependence on education outcomes. As particular studies about this topic are rare, I review both cross-country and within-country studies. Blanco and Grier (2012), for example, estimate the effects of 'resource dependence', measured as the share of exports of primary products in total GDP, on an education measure, using a panel of 17 Latin American countries from 1975 to 2004, averaged into 5 year periods. They find that resource dependence has no significant effect on the mean years of primary education completed by the population aged 15 or more.

A more recent study by Edwards (2016a) uses cross-sectional analysis in 2005 of 188 countries to examine the impact of mining's share in total GDP on educational attainment. Even though a cross country study results in more resource dependence measures being feasible, Edwards argues that mining's share in GRDP is a better proxy for resource dependence than mining's share in exports, as it reflects mining's contribution to the overall economy. Edwards finds that resource dependence increases the percentage of people with no education either using OLS or IV estimation, where he instruments for dependence using national per capita fossil fuel reserves as of 1971. In particular, a one percentage point increase in mining share leads to a 0.671 increase in the percentage of people with no education. For robustness, Edwards also looks at whether mining's share of GRDP undermines average years of education. He again finds a negative association, statistically significant at 1 percent level, using instrumental variables. He concludes that mining sector dependence is detrimental to education.

Moving to within-country tests of resource dependence and education, Weber (2014) tests for the South Central United States whether rising extraction of natural gas affects educational attainment of people at the county level. Weber considers education completion rates of the adult population. He finds that a change in natural gas production from 2000 to 2010 is positively associated with the proportion of adults who have completed high school and college education, and negatively associated with the proportion with less than high school education. In contrast, Douglas and Walker (2016) argue that resource booms, especially in (coal) mining, create an incentive for young people to leave school, reducing educational outcomes. Douglas and Walker test this view using panel fixed effects regression and employing a longer time period (1970-2010) for the Appalachian counties in the United States. They find that a higher coal mining intensity is associated with an increase of the share of young adults without high school diplomas and a decrease in the share that have bachelors degrees. These findings remain consistent in both OLS Fixed-Effects and under GMM-FE. This result is similar to that of Papyrakis and Gerlagh (2007) described earlier, though at state rather than county level.

Additional recent studies of resource use and education using United States counties have also been taken by Zuo, Schieffer and Buck (2019) and by Carpenter, Anderson and Dudensing (2019). Both studies use variation in number of oil and gas wells across counties to test their effects on education indicators. Zuo et al. (2019), for instance, use 1,170 counties within the 15 states that contribute almost 85% of overall oil and gas production in the United States. The authors use drilling density, defined as the share of the number of newly drilled oil and gas wells divided by total size of labour force in 2000, and also use the share of geographic shale formation over the county area as an instrument for potential endogeneity. Similar to Douglas and Walker, Zuo et al. find that higher drilling activity is negatively correlated with high school enrollments for grades 11 and 12 between 2000 and 2013.

For their part, Carpenter et al. (2019) select counties in Texas to examine the effect of oil-driven economic activities on high school drop-out rates. The authors use the number of newly operating oil wells or “spuds” to measure oil dependence. Newly operating wells are believed to have strong local employment effects as they require more labour to be hired than when wells are more established. Their start ups create incentives for young local residents to enter the labour market, which could potentially lower rates of high school enrollments. Using pooled OLS and panel fixed-effects regression over the period 2010-2014 in 203 counties and controlling for population and ethnicity (Latino and non-Latino), the authors find no evidence that general drop-out rates are affected by Texas’s dependence on oil, though drop-out rates for immigrant youth in particular are raised.

4.2.1.4 Effects on Health

With regards to resource effects on health, I find only a few cross-country and within-country studies. One between country study by Bulte, Damania and Deacon (2005) using 1971 cross-sectional data, finds that natural resources, either measured as point resources (exports associated with fuels and minerals) or diffuse resources (exports in conjunction with agricultural products), have no effect on life expectancy in 2001. More recently, Cotet and Tsui (2013) explore the effect of a country's oil dependence on two health outcomes: infant mortality and life expectancy. Interestingly, by using pooled cross-country regression over 1960-1980, Cotet and Tsui find that oil rents (defined as [production – cost] x global oil price) improve longevity within the population and reduces infant mortality. Cotet and Tsui also try instruments for oil dependence by using the product of oil production and initial oil reserves, and try country fixed-effects, and find similar positive results.

Another dependence study by El Anshasy and Katsaity (2015) distinguishes resource dependence by type (namely hydrocarbon, mineral, or agricultural) as a percentage of each country's GDP and test their effects on health outcomes in a cross-country study. These authors also find that in general oil rents improve health outcomes such as reductions in the rates of obesity and diabetes, while they have no effects on life expectancy. In contrast, dependence on agriculture has a positive effect on life expectancy and diabetes rates, but no effect on obesity. El Anshasy and Katsaity's regression approach is based on cross-section OLS regression for 118 countries, regressing health status in 2008 on resource intensity in 1980. Edwards (2016a) also exploits data among nations and uses IV with the limited information maximum likelihood (LIML) estimator by regressing life expectancy and infant mortality separately on mining's share in total GDP. In contrast to the previous studies, Edwards shows that a greater share of mining in total GDP significantly lowers life expectancy and is associated with increased rates of infant mortality.

Moving to within-country studies, as with Edwards (2016a) the results are less optimistic. Al Rawashdeh, Campbell, and Titi (2016) descriptively examine the case of cities within the Middle Eastern country of Jordan. They find that the value of mining per capita is positively associated with the rate of infant mortality. Unfortunately, Al Rawashdeh, et al. provide no regression analysis with controls, other than in simple bivariate form. More promisingly but not directly related with life expectancy, or infant mortality, Zhan, Duan and Zeng (2015) follow the provinces of China from 1999 to 2009 and control unobserved provincial effects under panel fixed effects regression. Zhan, et al. similarly find that an increased share of mineral industrial output in GDP reduces expenditure on overall health care (a combination of services from hospitals, community medical clinics for urban and rural areas, epidemic prevention, maternity and child care, and drug administration).

4.2.2 Spatial Effects in Economic Studies

Before I discuss incorporating spatial spillovers of resource dependence in section 4.2.3, I first explore why spatial effects have emerged in economic studies more generally. Traditionally, studies in economic growth have implicitly assumed that economic activities in one area are not affected by spatial factors, including activities occuring within close proximity. These studies define acceptable growth as a condition where greater production (led by many sectors) is achieved compared to the level of output in previous years. In famous conventional growth models (e.g. Temple (1999)), the rate of an area's growth is determined by its physical and human capital, and also by its rate of technological progress. In other growth models such as Barro (1991), initial income per capita also plays an important role in predicting convergence dynamics in growth rates between different areas. In both cases, factors relating to geographic spillovers are not accounted for.

In the 2000's, however, growth researchers began to incorporate geographical indicators which might also explain variations in countries's growth rates. For example Rodrik et al. (2004) argue that geographical factors alongside trade openess and institutions influence economic growth. Measures ranged from dummies regarding geographical features (e.g landlocked/remote), climate, latitude, or agglomeration externalities. While geographical features soon became widely adopted in empirical research (e.g. landlocked status in Sachs & Warner (1999); Acemoglu et al. (2005), Daniele (2011)), they were confined to absolute locational characteristics, rather than allowing for effects from adjacent jurisdictions.

Abreu, de Groot and Florax (2005) recognise this distinction in their survey of the growth literature by categorizing spatial effects as based on relative rather than absolute location. Factors such as longitude, latitude, being landlocked are categorised as absolute. In contrast, when relevant characteristics of the nearest neighbouring areas are taken into account, such as those areas that share a common border, they are known as relative factors. Absolute and relative spatial factors can act as complementary exogenous variables when trying to explain variation in growth between areas (Abreu, et al. 2005; Bosker & Garetsen, 2009).

Therefore, if spatial heterogeneity in absolute features affects growth and should be controlled for, then so too should spatial heterogeneity in relative features of surrounding areas, weighted by distance. As inspired by Tobler's Law that says that "near" things are more related than distant things, the relative notion of space based on proximity or neighbourhood effects has since become increasingly incorporated in regression analysis. An early exposition of a spatial econometric approach is provided by Anselin ((1988) in Anselin & Rey (2014)). Nearness of potential relevance is measured based on contiguity factors of neighbouring regions, based on the construction of spatial weights.[86]

The use of spatial spillovers has then spread from studies of growth to studies by urban economists and economic geographers. A paper by Moreno & Trehan (1997) is frequently cited as the first exploring spatial spillover effects on growth. These authors used spatial weighting and OLS regression to estimate whether relative locational proximity matters for long-term economic growth. They construct their weights using a distance-based neighbourhood, equally weighting all countries that share a border with the home region. Using a standard econometric model, this study finds that nearby countries that have larger markets than the home country contribute positively to the home country's growth. Similarly, Easterly and Levine (1997) investigate a spatial contagion effect on growth performance in which they find similar beneficial results of large neighbours.[87] Looking instead at contagion effects of civil war, Murdoch and Sandler (2016) find that the closer the distance between home country and adjacent neigbours that experienced civil war, the more negative the impact on growth in the home country.

Other studies have considered spatial spillover effects of other neighbour characteristics on home area growth. For example, Ades and Chua (1997) analyse the impact of political instability (measured using the mean annual number of revolutions and coups between 1960 and 1985) of neighbouring countries on home country per capita growth. Ades and Chua use the inverse of the number of neighbouring countries that share a border with

[86] These spatial weights are used to construct the "neighbourhood" for each unit of analysis, such as a county. Spillover effects can then be examined by testing whether outcomes of interest for area i are affected by explanatory variables for area i, and for its constructed neighbourhood.
[87] Spillover effects of neighbours with entreprenurial capital have also been investigated by Pijnenburg & Kholodilin (2014). These authors try to isolate the effect of knowledge spillovers on regional economic performance in Germany. Using OLS and a Spatial Durbin Model (SDM), they find their results are very sensitive to the choice of spatial weighting used.

the home country as each neighbour's equal weight, and then regress per capita GDP on domestic and neighbour political instability. They find a low correlation between domestic and neighbour instability, and that the effect of neighbour instability on domestic growth is significantly less than the effect of domestic political instability.

The spillover effects of the quality of neighbour countries' institutions on domestic growth has also been investigated. Bosker and Garretsen (2009), for example, seek to extend the analysis of Rodrik, et al. (2004) already mentioned by adding spatial institutional quality. Bosker and Garretsen use the simple average of neighbour country institution quality, where each contiguous country receives an equal weight. Bosker and Garretsen compare their results both under OLS and 2SLS on the basis of single year cross-section regression analysis. When using 2SLS, they instrument for both home country's institutional quality, and that of neighbouring countries. Bosker and Garretsen find that neighbour institutional quality significantly raises home country GDP per capita. In addition, when neighbour institutional quality is added, the effect of a country's own institutional quality remains significantly positive but smaller. This implies countries benefit not only from the quality of their own institutions but also from the quality of institutions of countries nearest to them.

4.2.3 Including Spatial Effects in Resource Effect Studies

As recognition of spatial spillover effects has grown in empirical analysis, resource effect researchers are also beginning to incorporate them. As mentioned in the introduction, a few studies looking for resource effects on income have included spatial effects, but none has done so when looking for resource effects on broader development outcomes. For these other outcomes I thus turn to review the importance of spatial effects from other cognate areas.

The existing resource curse/blessing studies focused on income that have tested spatial spillovers of which I am aware are by Carmignani (2014), Weber (2014), and Lee (2015), with a few others that I will discuss in turn.

A working paper by Carmignani (2014) is the first I know of that considers the effects of neighbourhood resource intensity on domestic income, though using country level data. Carmignani (2014) tests over 147 countries whether resource "intensity" (stock over GDP in 1970) in country *j* affects real domestic income growth in country *i* between 1970 and 2005. Carmignani measures the "neighbourhood" around "country *i*" as a weighted average of its contiguous neighbours. Specifically, he uses a spatial weight matrix W based on the fraction of shared border length of each neighbour of the home country, divided by i's total border length.[88] Concentrating on the outcome of real per capita GDP in 2005, Carmignani finds that, controlling for other geographical factors like landlocked status and latitude, and for initial per capita GDP in 1970, a home country's resource intensity has no significant effect on its GDP growth, while its neighbourhood resource intensity has a significant negative effect. That is, Carmignani finds a spatial resource curse, flowing from the resource intensity of a country's neighbours rather than from its own resource endowment.

The model developed by Carmignani is interesting because it is the first to allow the resource dependence of neighbouring areas to play a role. In the language of spatial regression analysis, the neighbourhood variable constructed is known as the spatial lagged explanatory variable, or an SLX model (Elhorst, 2010; Halleck Vega & Elhorst, 2015). However, Carmignani's model differs from a formal SLX model in considering the spatial lag of only his key variable, rather than all explanatory variables.

Beyond Carmignani's cross country study, the few other resource effects studies to control for spatial effects have been within-country, generally the United States (Weber, 2014; Deller, 2014; Lee, 2015; Douglas and Walker, 2016; and Weinstein, Patridge and Tsvetkova, 2018) or Australia (Fleming, et al. 2015). These studies mainly focus on the regional economic and development impact of oil, natural gas, or mining in general.

Weber (2014), as described previously, for example, aims to investigate the impact of natural gas production (in billions of cubic feet) on labour market outcomes such as total employment, employment in mining and manufacturing, population, and earnings per job, in the 362 counties of the south-central United States (Arkansas, Lousiana, Oklahoma, and Texas). Weber limits his focus to this region for greater homogeneity of unobserved features in the sample. Recognizing a lag from the time when gas is drilled to the time it becomes commercialised, Weber performs a difference in difference analysis substracting a change in 1995-2000 from the change of 2000-2010. Relevant here, Weber also adds spatial lagged gas production as well as spatial lags for all regressors, a full SLX model. Weber also tries instrumental variables for home and neighbour gas production using the location and growth in production of unconventional gas reservoirs in home and neighbour countries. Weber thus

[88] The weighted average is then created by a multiplication of the constructed spatial weight matrix with the resource intensity of neighbouring countries.

follows a similar IV strategy as that used by Bosker and Garretsen (2009) in their study of institutional quality spillovers.

In contrast to Carmignani, Weber finds no significant effect from the spatial lag of gas production on his various dependent variables, except for earnings per job which is negatively affected. Interestingly, Weber finds that the change in earnings in the home county is greatly affected by change in gas production in its neighbourhood, though the domestic effect of gas production is positive. Regarding the impact on education, Weber finds no evidence that the spatial lag of gas production affects a home county's education completion rates, looking specifically at the adult population who separately completed less than high school, high school, college and more. Weber thus finds a resource blessing for various development outcomes, such as educational attainment of the adult population, but not from spatial spillovers effects *per se*.

In a similar vein, Lee (2015) adapts Weber's study, restricting attention to Texas, but extending it to include oil dependence effects on the local economy. Using annual county-level data, Lee begins his baseline model using a 2014-2009 first-differenced model where he uses numbers of active oil or gas drilling wells as the key regressor, and considers the effects on local employment and income over the 6-year period. Lee also considers county fixed effects. Finally, Lee considers a spatial panel model by including a weighted average of all explanatory variables in neighbouring counties, as done by Weber (2014). Lee arranges his spatial weight based on simple contiguity (i.e. all counties contiguous with the home country are equally weighted). Lee finds in his non-spatial fixed effects model that the number of oil and gas wells has a positive and significant effect on employment and income. The estimated effects are consistent whether oil and gas are considered separately or aggregated. The results are fairly similar with regards to a cross-section 2014-2009 first-differenced model. In the final spatial model, Lee differs from Weber in finding that an increase in oil and gas wells in neighbouring counties raises home county employment and income.

Douglas and Walker (2016) also consider spatial effects for the effect of coal dependence on long term income growth (1970-2010) in the Appalachian counties of the United States. Douglas and Walker also use simple equal weighted contiguity for their spatial weight matrix, as applied in Weber and Lee, to construct their spatially lagged regressors. Using GMM estimation, Douglas and Walker find that both home county coal dependence and its spatial lag have negative and significant effects on annual growth.

Lastly for the United States, a recent study by Weinstein, Patridge & Tsvetkova (2018) extends the studies by Weber and by Lee, examining the effects of oil and gas well proliferation on oil and gas earnings as well as employment. Unlike the previous studies, Weinstein et al. also create a spatially lagged dependent variable. In particular, they include energy earnings growth in bordering counties to capture spatial spillover effects of the dependent variable on home county earning growth. They use the same difference-in-difference strategy for 2001-2013 as Weber (2014) and Lee (2015) and divide the sample between metropolitan and non-metropolitan areas within all 48 states of the continental United States. Weinstein et al. find that counties that are surrounded by oil and gas dependent neighbours receive a small positive effect on their earnings. Metropolitan areas tend to be more affected than non-metropolitan areas. The results are similar when they use an instrumental variable approach, using the abundance of oil and gas endowments across counties.[89]

In one non-United States study, Fleming, Measham and Paredes (2015) control for spatial effects when studying the effect of mining employment on median family income and non-mining employment in Australia. Fleming at al. use 449 non-metropolitan local government areas (LGA), using census data in 2001 and 2011. The authors, however, control for spatial neighbourhood effects not for the key variable of interest, but instead for other initial year control variables such as the unemployment rate, population, and family median income in adjacent LGAs. Fleming, et al. find that an increase in mining employment positively affects both changes in family income and non-mining employment. They also find that spatial lags of other related control variables tend to positively affect both respective dependent variables.

To my knowledge, no resource effect studies have yet controlled for spatial effects in a developing country in general, nor Indonesia in particular. The closest relevant study for Indonesia has been a within-country growth study by Vidyattama (2014), which tests if the spatial lag of growth in neighbouring provinces affects home province growth. Vidyattama (2014) uses a spatial autoregressive lag model (SAR) of growth in the nearest neighbourhood, and then considers a spatial autoregressive error model (SEM). The author selects distance-based weighting to form a spatial weight matrix, using the distance between the geographic

[89] Weinstein, et al. (2018) use five instruments that can approximate for the level of oil and gas abundance: percent of a county area over a shale play, estimated amount of recoverable shale gas, estimated amount of recoverable tight oil, thickness of a shale play, and intensity of drilling in the 1980's.

centroid of each province. Albeit not related to resource effects, this study provides an attractive alternative method for identifying neighbourhoods.

Not surprisingly, with the few resource effect studies that have included spatial effects, there is as yet no firm consensus as to their relevance, nor to the best way to construct neighbourhoods. Counter-examples to Tobler's law can be found. For example, Abderrezak (2005) finds that the growth rates of Algeria, Morocco and Tunisia are more affected by the growth rates of distant countries than by that of adjacent neighbours.

With no evidence regarding spatial spillovers of resource dependence in developing countries, I turn now to my investigation for Indonesia using similar approaches to neighbour construction as used by recent studies.

4.3 Data and Empirical Estimation Strategy

4.3.1 Data

Most of the data for this investigation are obtained from the Indonesia Central Bureau of Statistics (BPS) and the Indonesia Database for Policy and Economic Research (INDO-DAPOER) from the World Bank. Data from BPS is freely accessible though for some indicators it must be purchased at the household level from Indonesia's National Labour Force Survey (Sakernas) or National Social Economic Survey (Susenas) and then aggregated to district level.[90] I also use data obtained from relevant publications across ministries of the Republic of Indonesia, e.g. from the Ministry of Energy and Mineral Resources (MoEMR), the Ministry of Finance, and from the National Audit Board (Table A1 in Appendix 4.1 compiles a full list of variables used and their definitions).

These data will be used to provide measures of district-level resource dependence, and control variables such as the change in labour force participation rate, initial district income per capita and initial local population of each district, as well as earthquake incidence. The period of observation is generally between 2006 and 2015, with 2005 values used as a baseline period, though in some cases of limited data availability, 2007 is both the initial year, and the start point of 2007-2015 differences.

The reasons the district level data are restricted to 2006 onward is primarily data availability and reliability. District data was not available at sufficient completeness prior to

[90] I use this survey to construct educational attainment at district level as my alternative dependent variable.

the implementation of decentralisation in 2004-2005. One challenge of following districts over time has been the splitting of 'parent' districts into 'child' districts between 2007 and 2014, a proliferation allowed under decentralisation. To follow districts consistently over time, I collapse 'child' districts back to their parent districts, reducing the number of districts to 390.

As absolute geographical factors tend to be controlled for in the broader growth literature (e.g. Rodrik et al. (2004); Bosker and Garretsen (2009), Carmignani (2014), Weber (2014), Fleming and Measham (2015)), I will also control for them here. I thus collect data on three geographic measures for each district: (1) a dummy if it is landlocked; (2) the straight line distance between its centroid and that of its corresponding provincial capital, and (3) the distance between its centroid and that of Indonesia's capital Jakarta.[91] These variables are constructed using the shapefile data of Indonesia's administrative district map taken from the Indonesia Survey and Mapping Board (Bakosurtanal) and the Indonesia Geospatial Board (BIG), modified to the 390 district boundaries used in this study. This approach thus covers all original (as of 2003) 'parent' districts in Indonesia consistently over time.

As foreshadowed, a key methodological objective of this chapter is to allow for spatial spillover effects when examining the effect of resource dependence on income and other development indicators in Indonesia. As a result, constructing a spatial weights matrix to identify the 'neighbourhood' of each district plays a key role in my analysis. For robustness, I use three spatial weighting methods and resulting matrices. I will describe these thoroughly in the next section, but in summary they are based on: (1) *a simple queen contiguity weight*; (2) *a length-border based weight*; and (3) *a centroid distance based weight*.

To pursue my other key objective for this chapter. I analyse the impact of resource dependence beyond its effect on per capita income, to also consider effects on poverty, education and health. For data related to the poverty rate, I use the proportion of individuals having expenditures below the poverty line following Bhattacharyya and Resosudarmo (2015) and Miranti (2017). This poverty data comes from BPS, derived from the National Socio-economic Survey (Susenas). For education outcomes, I use district data on the highschool and university graduation attainment of adults. This information is constructed

[91] Measuring distance using physical features such as road length is difficult given the nature of the Indonesian archipelago.

from household level data at each district, sourced from Sakernas starting only in 2007.[92] For health outcomes, I use district level life expectancy information. Data for life expectancy are taken from Human Development Publications published regularly by BPS.

4.3.2 Estimation Strategy

I will use three econometric models to estimate the effects of resource dependence on development outcomes. I begin with a baseline first-differenced regression model without controls for spatial spillovers. I will then include a spatial effect only of my key resource dependence measure. Finally I will include spatial lags of all independent variables as discussed by Vega and Elhorst (2015). To be able to estimate spatial spillovers, I begin by explaining how I construct various spatial weights matrices that are used to create a 'neighbourhood' for each district.

4.3.2.1 Constructing Spatial Weight Matrices

A spatial weights matrix (W_{ij}) is a key element for conducting spatial analysis in regression models. For a study of N areas, W_{ij} contains information of dimension $N \times N$. Each row of the matrix provides information concerning the importance (relatedness) of area *i* to each of its neighbours (e.g. countries, regions, districts, etc.). Each column provides information concerning the importance of each of its neighbours to *i* (Anselin & Bera, 1998).

The size of the matrix is thus sensitive to the number of areas being used here, 390. Depending on the exact weighting criteria, many districts will have no measured relatedness to another. For Indonesia in particular for some weighting rules some island districts will have no 'neighbourhood', affecting the sample size in regressions with spatial lags.

As the purpose of constructing $W_{i,j}$ is to weight the impact of nearby districts, and by definition each district has zero distance from itself, the diagonal elements of (W_{ij}) are zero. Table 4.1 illustrates.

Table 4.1. An Illustration of Spatial Weighting Matrix $W_{i,j}$

	District A	District B	District C	District D
District A	0			
District B		0		
District C			0	
District D				0

[92] The Sakernas data samples representative households from every province in Indonesia. This survey only claims representative sampling at district level in 2007, 2010, 2015 and 2018.

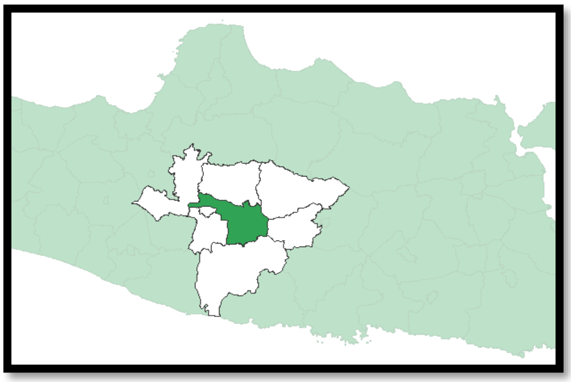
As foreshadowed in section 4.3.1, this study exploits three different weighting rules separately for each regression model as a check for robustness. Following the standard literature in this area, these weighting rules vary from the basic queen contiguity rule to one of two distance-based weights, using a specific bandwidth from home district to define eligibility.

4.3.2.2 The Queen contiguity weight

The first spatial weights matrix (SWM) is simple and commonly used in econometrics analysis. As pointed out in Anselin & Bera (1998), or recently Anselin and Rey (2014), the "queen contiguity" treats districts i and j as neighbours if they share any common border.[93] All adjoining districts to district i are then equally weighted to define i's neighbourhood.

More specifically, a binary matrix is used initially, where if district *i* (in Figure 4.1, the district with the dark green colour) shares any land border with another district, the matrix value for those districts are 1, and 0 otherwise.[94]

Figure 4.1. Neighbours based on queen contiguity



To construct this weight, I used shapefile data of the 390 districts in Indonesia (as of 2003) to carefully identify the neighbours of each home district.

The binary contiguity matrix constructed using this rule is then normalised by a row standardisation which effectively gives an "equal weight" to each contiguous neighbour of a home district. Thus, the elements of a row-standardized weights matrix are $w_{ij} = w_{ij}/\sum_j wij$

[93] The term "queen" is inspired by the chess game where the queen can move in any direction, including corner moves (Anselin & Rey, 2014). In general, most studies applying spatial analysis will try this weight first before moving to another weighting rule to check robustness.
[94] A related, but less common rule is "rook" contiguity, where areas sharing only a corner point in common with the home area are excluded as neighbours.

(Anselin & Bera, 1998). This weighting method has also been used in Weber (2014), Lee (2015), and Weinstein, et al. (2018). It is simple, but has the disadvantage of treating as equally important neighbours who may vary greatly in their border overlap with the home district. In addition, Queen contiguity excludes island districts who lack adjacent districts.

4.3.2.3 Length of border-based weight

Though less common, I also try two alternative weighting rules that place greater weight on 'nearer' neighbours than on more distant ones. The first is based on the proportion of a home district's total border that is shared with each adjacent neighbour (Carmignani, 2014; Carmignani and Kler, 2016; Murdoch and Sandler, 2016). ArcGIS is used to measure the length in kilometres of the border that district i shares with each adjacent district. The border length of district i is used as the denominator. Note that for districts who partially border the ocean, that coastal length of border will not be counted in the denominator.

More formally, following Ades and Chua (1997) and Carmignani (2014), the length-of-border weight assigned to neighbour *j* of home district *i* is:

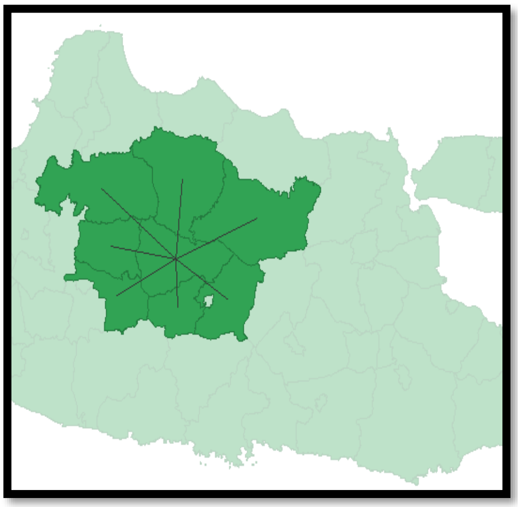
$$W_{ij} = \frac{l_{i,j}}{\sum_j l_{i,j}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Here $l_{i,j}$ is the length of the land border between districts i and j. The length-of-border weighting matrix has the advantage of giving greater weight to adjacent districts that share more of districts i's border. Nonetheless, for a country like Indonesia, the largest archipelagic nation in the world, there remains the problem that districts that are physically surrounded by the sea are classed as having no neighbours and are thus ineligible for spatial analysis. This can be handled as in Carmignani (2014), by excluding such districts from analysis throughout. This ensures consistent treatment, but reduces the number of districts observed.

4.3.2.4 Distance-based weight

A third approach for weighting neighbours uses the distance between the 'centroid' of a home district and the centroids of nearby neighbours within some pre-determined radius. Arbitrarily, I use 200 km as my centroid threshold radius to select which districts are eligible to be treated as neighbours as illustrated in Figure 4.2. I choose this radius because the average centroid distance between some remote non-populous districts in Indonesia does not exceed 250 km. This means that most, but not quite all, island districts can have a neighbourhood classified using this distance.

Figure 4.2. Weight based on centroid point distance with 200 km radius limit



Following studies such as Gamboa (2013), Pijnenburg and Kholodilin (2014), Yildirim & Öcal (2016), and Gerolimetto and Magrini (2016), the latitude and longitude of the centroid point of each district can be identified, and then the distance between the centroids of each home district and its neighbours.

Eligible neighbour districts are assigned weights that take the form of the inverse of the distance between centroids, or $w_{i,j} = 1/d_{i,j}$, such that nearby districts with closer centroids receive more weight. The weights are then row normalized to sum to 1, i.e. $w_{i,j} = \frac{1}{d_{i,j}} \Big/ \sum \frac{1}{di,j}$.

This method identifies neighbours for island districts, so long as the distance between their centroids is within 200 km (see e.g. Bosker and Garretsen, 2009).

4.3.3 Empirical Strategy

4.3.3.1 First-Difference Model: Non Spatial Regression

To begin, I perform my analysis using an ordinary least squares (OLS) first-difference model over two different periods of time to control for unobserved heterogeneity across districts that may affect growth (Wooldridge, 2016).[95] I use a 9 year difference, $t_{2015} - t_{2006}$.

[95] To see the equivalence between two period fixed effects and first difference models, I can follow Wooldridge (2016) and take the difference of panel data across two years, t and $t - 1$.

For any given outcome of interest, I run my FD model first without and then with spatial effects, initially just for resource dependence, and then for all explanatory variables. This is a resource effect specific-to-general approach (Elhorst, 2010) and has been implemented in resource effect studies such as Lee (2015) and Weber (2014).

Beginning with growth in income, my initial specification is as follows:

$$\Delta Ln(GRDP_i) = \gamma + \Delta RD_i\beta + \Delta X'_i\,\sigma + \Delta\varepsilon_i \qquad \text{.........................} \qquad (3)$$

Here $\Delta Ln(GRDP_i) = ln\big(GRDP_{i,2015}\big) - ln(GRDP_{i,2006})$, and measures the difference in log GRDP between 2006 and 2015. For other development indicators, I will use the change in district poverty rate ($\Delta Poverty$), the change in education attainment ($\Delta Educ_i$), measured as the proportion of the district population aged 15 or over that has at least graduated from high school, and the change in the log of life expectancy ($\Delta Lifeexp$).

$$\Delta Poverty_i = \gamma + \Delta RD_i\beta + \Delta X'_i\,\sigma + \Delta\varepsilon_i \qquad \text{.........................} \qquad (4)$$

$$\Delta Educ_i = \gamma + \Delta RD_i\beta + \Delta X'_i\,\sigma + \Delta\varepsilon_i \qquad \text{.........................} \qquad (5)$$

$$\Delta Lifeexp_i = \gamma + \Delta RD_i\beta + \Delta X'_i\,\sigma + \Delta\varepsilon_i \qquad \text{.........................} \qquad (6)$$

For compactness, each dependent variable can be more generally labelled $\Delta OUTCOME_i$.

The key explanatory variable in models (3) to (6) is ΔRD_i. As in previous chapters, I use four alternative measures to capture the extent to which each district is dependent on point source type natural resources such as oil, natural gas, and coal. These measures are MINDEP, which is the share of oil, natural gas and coal including other minerals in district GRDP, district government dependence on oil and gas revenues (OILGASREV), which is the share of local government budget revenues deriving from oil and gas rents and royalties, district government dependence on coal revenues (COALREV), defined analogously, and finally district government dependence on oil, gas and coal revenues combined (MINREV).[96] The $\Delta X'_i$ stands for a set of control variables, including changes in the labour force participation

[96] I follow Edwards (2016a,b) in the use of MINDEP and Cust and Rusli (2016) in the use of budget dependence measures. I acknowledge that some papers cited have used the number of oil or gas wells as a dependence measure for the county-level case in the U.S. However, due to incomplete information regarding changes in oil wells across districts over time, this approach can not be followed here.

rate, initial population level (in logs), and the cumulative incidence of earthquakes between 2006 and 2015. Additional controls are included to capture the absolute geographic position of districts, namely urban status (if a municipality) (DURBAN), location on Java Island (DJAVA), and whether districts lack coastal access (LANDLOCKED). I also control for the absolute distance of the centroid of each district from its provincial capital (DIST_PROV), as well as from the national capital Jakarta (specifically the Indonesian Presidential Palace) (DIST_NAT). All distance measures are in km. The ε_i is the idiosycractic error term that reflects omitted variables.

As commonly used in growth models and the resource effects literature, I also control for the baseline conditions (BASELINE) of each outcome of interest in 2005, whether the log of GRDP per capita in 2005, or the log of poverty rate or education or life expectancy measures. I follow Barro (1991) in including initial income per capita as an explanatory variable to capture its long term effects on change in GDP, and a possible convergence effect. Controlling for baseline income per capita is also common in resource effect studies (e.g. Sachs and Warner, 1995; Douglas and Walker, 2016; Edwards, 2016a).

As has become standard in the resource effects literature, I also address the possible endogeneity of my resource dependence measures, ΔRD_i, by using instruments.[97] I use two categories of instruments: historical measures of resource abundance, RA_{1970s}, and changes in physical resource output. Specific combinations of these instruments will be applied depending on the resource dependence measure considered and the outcome variable in question (see Appendix 4.2 Tables A2 and A3 for the list of instruments used). Both types of instruments have been commonly used in resource effect investigations (e.g. Edwards (2016), Cust and Rusli (2014), Weber (2014), Caselli and Michaels (2013)). More details about the *ex ante* appropriateness of these instruments can be found in Chapter 1 (or 2).[98]

When instruments are used, the first and second stages can be expressed as follows:

$$\Delta RD_i = \phi + \gamma RA_{1970s} + \gamma \Delta OIL_i + \gamma \Delta GAS_i + \gamma \Delta COAL_i + \Delta X'_i\, \beta_2 + \Delta \varepsilon_i \quad (7)$$

[97] Some researchers argue that when it comes to the local level, mining dependence measured at the regional level can be treated as exogenous (Edwards, 2016a; Fleming, et al., 2015).

[98] By looking at the 2005 maps provided by the Indonesian Ministry of Energy and Mineral Resources showing the main locations and comparing it with earlier and later maps, it is clear that no dramatic shifts have occurred. Thus, there is no way for district governments to experience resource windfalls in 2015 without having had successfully proven deposits in the 1970's and early 1980's.

$$\Delta OUTCOME_i = \gamma + \pi_1 \Delta\widehat{RD}_i + \Delta X'_i\, \pi_2 + \Delta\varepsilon_i \qquad (8)$$

An instrumental variable method based on the two steps GMM (IV-GMM) is used to perform this regression using the *ivreg2* command to ensure all stages are correctly calculated and standard errors are robust in the presence of heteroskedasticity. When the instruments employed are sufficiently strong, and endogeneity problems occur, the IV-GMM estimator is preferred to OLS. Validity tests for weakness will be checked using the first-stage regressions using the F-statistics following Staiger and Stock's rule of thumb (Wooldridge, 2016), while Hansen's *J* statistic will be used to test whether instruments are overidentified, which is a necessary condition for being uncorrelated with the error term.[99] To be conducted, overidentification tests require the number of instruments to exceed the number of suspected endogenous regressors. Endogeneity tests are run using the Hausman-type *endogtest* in Stata *ivreg2*.

4.3.3.2 Controlling for Resource Dependence in Neighbouring Districts

From baseline first difference models (with and without instruments), I next turn to accomodate the potential spatial spillover effects of the resource dependence of neighbouring districts on home district outcomes of interest. Using the spatial weights matrices decribed in section 4.3.2.1. to define the neighbours, I extend the first difference models expressed in Eq. (3)-(6) by including variables that can capture variations of resource dependence in the neighbourhood of own district *i*. This enters as a multiplication of the spatial weights matrix (W) with the matrix of district ΔRD_i.[100] This creates a spatial lagged variable that is defined as the weighted average of resource dependence in the neighbourhood areas of district *i*.

This approach follows Carmignani (2014), and is similar to Weber (2014) and Lee (2015), though the latter papers also include spatial lags for all independent variables.

We can write this extension formally as:

$$\Delta Outcome_i = \sigma + \Delta RD_i\beta + \Delta RD_N\theta + \Delta X'_i\, \sigma + \Delta\varepsilon_i \quad .... \qquad (9)$$

[99] I use the ***ivreg2*** command in the Stata module developed by Baum, Schaffer, and Stillman (2007). The ***ivreg2*** command provides diagnostics to check for instrument relevance and overidentification.

[100] Elhorst (2010) offers a cross-section spatial model as $Y_i = \rho WY_i + X_i\beta + WX_i\theta + u$, also known as the Spatial Durbin Model (SDM) for panel data. The WY_i and WX_i capture the spatial lagged effects of the dependent variable and explanatory variables, respectively. I do not include spatial lags of the dependent variable.

where RD_N is the spatial lag of RD_i , subscript i represents own district and N corresponds to i's neighbourhood. The equation can thus test the direct effect of spatial spillover captured by θ on each dependent variable, $\Delta Outcome_i$.

As explained in Bosker and Garretsen (2009) and Weber (2014), if endogeneity is a concern for a home district variable, then it is also a concern for the spatial lag of that variable. I will therefore instrument for RD_N as I do for RD_i. This is the approach taken by Bosker and Garretsen (2009), Weber (2014), Lee (2015), and Weinstein, et al. (2018). I will thus use the spatial lag of historical measures of resource abundance, RA_{1970s}, for oil, gas and coal, and for changes in physical resource output as instruments for RD_N. Here again the precise combination of abundance and production change instruments used will differ depending on the resource dependence and outcome measure used (see Appendix 4.2 Tables A2 and A3).

4.3.3.3 Controlling for Spatial Lags of the Explanatory Variables

As a final step, rather than testing for neighbourhood effects for only the key variable of interest, ΔRD_i, I will also include spatial lags of all explanatory variables as a robustness check. Controlling all spatial lags for independent regressors allows me to check whether spatial spillovers associated with resource dependence measures persist. This model is believed to be a good choice as a point of departure into spatial econometrics as it imposes less complexity compared to the inclusion of a spatial lag of the dependent variable (e.g. the SAR model of Anselin (Anselin & Bera, 1998)). The spillover effects captured by this model are more straightforward to interpret (see Elhorst (2010), Halleck Vega & Elhorst (2015), and Elhorst & Vega (2016), Gibbons and Overman (2012)).

Numerous recent empirical studies which include spatial spillovers have used the fuller spatial lag of X (SLX) model with all explanatory variables (e.g. Weber (2014); McCoy, Lyons, Morgenroth, Palcic, & Allen (2018); Araújo, Goncalves, Almeida (2018)).[101] In contrast to standard OLS, the SLX model estimates for each explanatory variable both its direct effect on the outcome of interest, and its indirect effect via neighbouring areas. The direct effects refer to the coefficient estimates of the non-spatial variables, whereas the spillover effects are those associated with the spatially lagged explanatory variables (Elhorst, 2010; Vega and Elhorst, 2015; Elhorst and Vega, 2016). Note, however, that when the spatial

[101] Another reason to use SLX is that there is still debate about the interpretation of spillovers in the Spatial Lag Model using the autoregressive (SAR) or error (SEM) forms (for additional detail, see Elhorst (2010); Halleck Vega and Elhorst (2015)).

lags of all explanatory variables are included, the estimated direct effects are not simply equivalent to the β_k in a model without spatial lags, such as OLS (Vega and Elhorst, 2015).

The SLX model takes the form:

$$y_i = X\beta + WX\theta + \varepsilon_i \ \ldots\ldots\ldots \tag{10}$$

here W is the SWM containing N elements of the $N\ x\ N$ non-negative matrix, and WX identifies the weighted average neighbour characteristics for all expanatory variables. These indirect effects are estimated by θ. This model assumes no autoregressive component $\rho = 0$, but that $\theta \neq 0$ as discussed in Vega and Elhorst (2015). With regards to potential endogeneity of some explanatory variables, the SLX model can use standard instrumental variable techniques such as 2SLS or IV-GMM for both X and WX variables suspected of endogeneity.

Applied here, the SLX model becomes :

$$\Delta Outcome_i \quad = \quad \eta + \beta(\Delta RD_i) + \theta(\Delta RD_N) + \Delta X'\sigma + W\Delta X'_i\delta + \Delta\varepsilon_i \tag{11}$$

here $W\Delta X'$ represents the spatial lag of all other explanatory variables for the neighbourhood of district i. Again I will focus on the parameters β, θ, and δ, which capture the relevant impacts of resource dependence and its spatial lag.

4.4 Results

Table 4.2 reports information related to key variables used in subsequent regression analysis. To highlight, growth in per capita GRDP has shown a positive trend, with a 41.4 % increase on average between 2006 and 2015. The average change in the share in poverty has been a drop of 6.2 % on average, while life expectancy (expressed in logs) has increased on average by 2 percent (or without a logarithmic transformation, it has increased by 1.54 years). Educational attainment has also generally improved, with an average 11.5% increase in the share of the local population having at least a secondary school degree between 2007 and 2015.

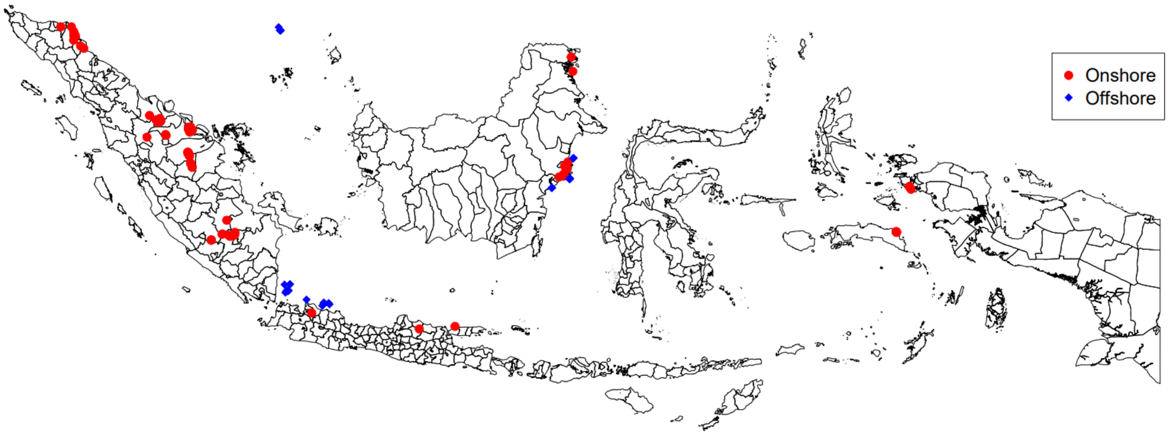
Table 4.2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ Real GRDP per capita (in logs)	390	0.414	0.345	-0.852	2.685
ΔMining Dependence	390	0.012	0.142	-0.614	0.795
ΔOilGas Revenue	390	-0.029	0.091	-0.528	0.224
ΔCoal Revenue	390	0.015	0.048	-0.119	0.359
ΔMining Revenue	390	-0.013	0.084	-0.523	0.256
ΔPoverty rate	390	-0.062	0.073	-0.272	0.536
ΔLife expectancy (log)	390	0.020	0.044	-0.158	0.119
ΔEduc_attain	390	0.115	0.079	-0.190	0.393
Distance to prov. capital	390	136.962	132.930	0.000	718.173
Distance to Jakarta	390	1163.885	850.831	19.033	3787.245
Landlocked	390	0.087	0.282	0.000	1.000
DURBAN	390	0.208	0.406	0.000	1.000
DJAVA	390	0.303	0.460	0.000	1.000
Population, 2005 (in logs)	390	3.937	0.704	1.951	7.684
GRDP per capita, 2005 (in logs)	390	12.721	1.029	9.450	15.227
Instruments:					
oilgasabundance	390	0.154	0.660	0	7
coalabundance	390	3.660	14.327	0	94.214
Δoilprod	390	-103.164	3805	-22751	64381
Δgasprod	390	267.544	31094	-402890	378035
Δcoalprod	390	92.619	508.369	-45.277	5845.853

Note: see Appendix 4.1. Table A1 for a full list of variables and definition.

For illustrative purposes, Figure 4.3 depicts the location of oil wells over the 390 districts of Indonesia as of 2003. The wells are those classified as "development wells", defined as non-exploration wells associated with drilling activities over at least the last 5 years. Gas wells are also added in Figure 4.3. The districts containing these productive oil and gas wells are identified according to annual accumulated production data, which is used by the government for a post-decentralisation funding formula. That is, oil and gas activities in the point-of-origin districts generate resource windfalls that they use to fund the provision of local public services and transfers.

Figure 4.3. Oil and Gas Wells (Onshore and Offshore)



Source: *MoEMR, modified into map by author.*

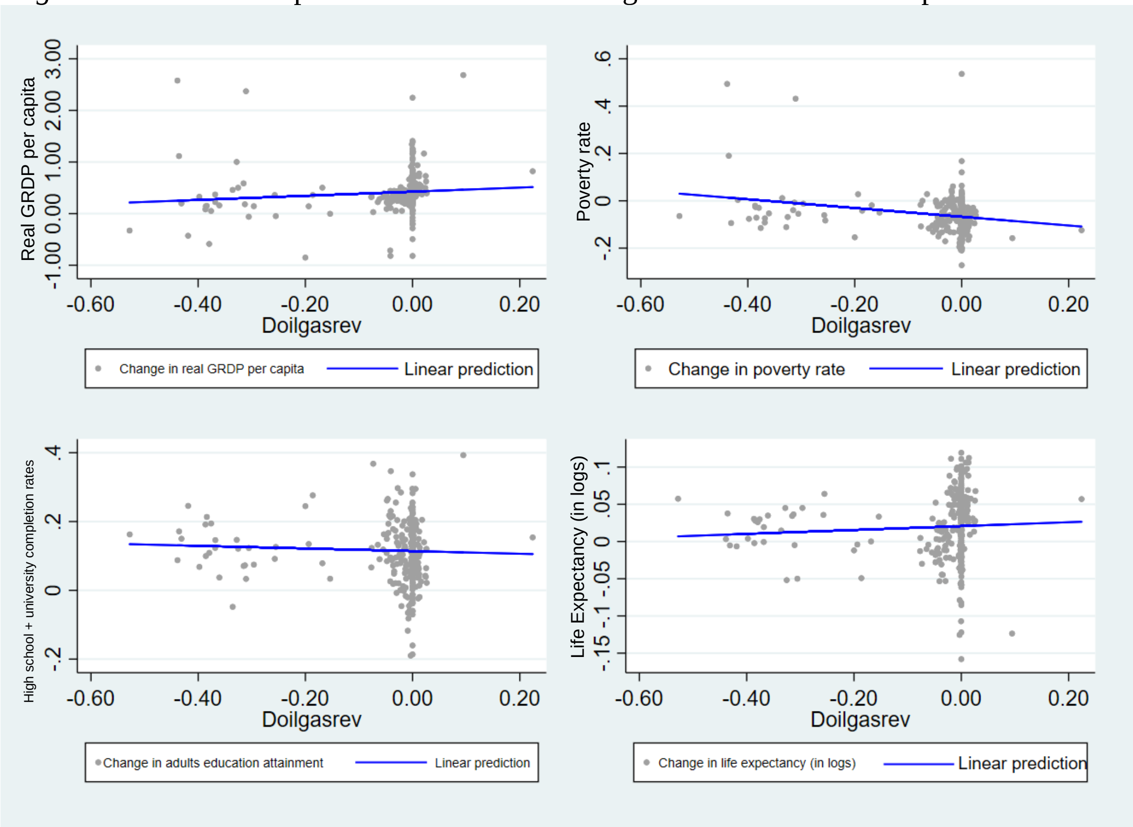
While I could obtain data on the number of wells in each district, I could not access the exact date at which each well began operation, nor the amount of oil or gas produced per well. Instead, I could access the total physical production from all wells per district.[102] As a result, I cannot identify variations in active wells over the time period of this study. As shown in Figure 4.3, most wells are located onshore rather than offshore, with a majority concentrated on Sumatra and Kalimantan Islands (see Appendix 4.3 Figure A1, for the names of Indonesia's islands). Significantly, these figures are very similar to the maps illustrated by Bee (1982), Leeuwen (1994), and Friederich & Leeuwen (2017), which I use to correlate historical oil and gas field locations in the 1970's with Indonesia's district boundaries map in 2003. This suggests that over 50 years of oil and gas discoveries in Indonesia, vital well locations have spread slightly, but are still predominantly concentrated over the same islands as previously.

I would therefore argue that the locations of these active wells represent exogenous variation in oil and gas-based activities based on abundance. There is no tendency for drilling activities to increase when district growth or education increases, nor when poverty rates change. The fact that most wells are located onshore is also not surprising, as the cost to construct and operate offshore wells for deep sea explorations is estimated to be USD 100-

[102] I illustrate the position of every well from https://geoportal.esdm.go.id of the Ministry of Energy and Mineral Resources. There are 583 oil wells (with development type) in total. Of these 269 wells are onshore for oil and 43 wells are offshore, while the rest are classified as non-producing new fields. For gas, there are approximatey 88 wells.

120 million per well to operate, with no guarantee that oil will be found at the desired level for commercial production.

Figure 4.4. Relationship between share in oil and gas revenues and development indicators



Source: *Author's construction*

I next present simple scatter plots of the change in oil and gas revenues' share in district government budget versus each development outcome of interest (change in local GDP (in logs), poverty, educational attainment, and life expectancy (in logs)). As highlighted in Figure 4.4, oil and gas dependence shows a slight positive relationship with local income and with life expectancy, and a negative relationship with the poverty rate, (i.e. with a decrease in the proportion of the population below the poverty threshold). In contrast, there appears to be a negative relationship between oil and gas dependence and attainment of at least high school completion across districts.

To test these associations between resource dependence and development outcomes more formally, I move next to regression results. I begin without spatial effects, then include spatial effects of resource dependence only, and finally allow for spatial effects of all explanatory variables.

4.4.1 Result 1: The Effects of Resource Dependence on Development Indicators Without Spatial Lags

This section considers the effects of resource dependence in Indonesian districts on development indicators as described in Section 4.3.3.1. I begin without spatial effects. Table 4.3 presents resource effects on the first outcome: local GDP (GRDP) per capita. Again I present first difference models to remove district fixed effects and then IV-GMM to account for potential endogeneity of my measure of resource dependence. With a greater emphasis on spatial factors in this chapter, I now also control for three absolute geographic factors as controls.

For efficient exposition, I move first to the instrument validity and endogeneity tests provided in IV-GMM results. Using the instruments listed in Appendix 4.2. Table A2, I find as in Chapter 1 that in all specifications (5) – (8), the instruments are individually significant in first stage regressions, and that the majority of first-stage *F* statistics are at or well above 10, suggesting that the instruments are sufficiently strong. Overidentification tests based on Hansen *J* also fail to reject the null, meaning that my instruments for each resource dependence measure pass necessary conditions for validity. Using these instruments, p-values in endogeneity tests shown show that three out of four measures of resource dependence are endogenous, leaving the preferred specifications to be (1), (6), (7) and (8). Here, again as I found in Chapter 1, an increase in budget dependence on resources significantly raises GRDP per capita for three of four resource dependence measures, showing a blessing effect on growth. For example, from (1), an increase in mining's share of district GRDP significantly increases GRDP per capita. In particular, a standard deviation increase in a change in mining's share is associated with a 10.5 (=0.141*0.745 = 0.105) percent increase in income per capita. Only rising coal revenue dependence is not associated with a rise in income.

Next, Table 4.4 reports the OLS estimates of resource dependence on change in the poverty rate, change in educational attainment and change in life expectancy. Corresponding IV-GMM results are presented in Table 4.5. I begin again by examining the validity of my instruments, and results of tests for endogeneity. As seen from the IV-GMM estimates in Table 4.5, the first-stage *F* statistic for each resource dependence measure for all outcomes generally exceeds 10, with the exception of columns (10)-(11) for life expectancy. Particularly for column (11) (life expectancy) this may raise the issue of weak identification, where my instruments are only weakly correlated with GRDP resource dependence. However, the p-value of jointly excluding the instruments for either of these two specifications shows them to be jointly significant, which indicates that the instruments are at least significantly correlated with the specified resource dependence measure. The p-values of Hansen *J*-statistics indicate that the instruments used have passed the over-identification test for all resource dependence measures where they can be run, with values ranging from 0.188 to 0.810. Note that for specifications in columns (7) and (11), the p-values cannot be calculated as the specifications become just-identified. Tests for endogeneity shows that, except for columns (1), (7), (10) and (11), the p-values can not reject the null hypothesis that resource dependence measures are exogenous for these broader development outcomes, suggesting that the OLS estimator is preferable. The preferred specifications are thus columns (2), (3), (4), (5), (6), (8), (9) and (12) from Table 4.4 and columns (1), (7), (10) and (11) from Table 4.5.

Moving to the results, neither in OLS nor in IV-GMM do I find that the poverty rate (columns (1) – (4)) is significantly influenced by variations in resource dependence. The insignificant effects imply that the blessing effects of resource reliance on local GRDP per capita have not been transmitted to improving living standards for people with the lowest incomes. Even more striking than resource dependence's lack of effect on poverty, all measures are negatively associated with the share of the local population at least completing high school, though generally only significant at the 10% level in columns (5) – (8) of the relevant table.

Table 4.3. OLS and IV-GMM, Dep Var: ΔGRDP per capita (log)

VARIABLES	(1) mindep	(2) oilgasrev	(3) coalrev	(4) minrev	(5) mindep	(6) oilgasrev	(7) coalrev	(8) minrev
ΔMindep	0.745***				1.359***			
	(0.191)				(0.466)			
ΔOilgasrev		-0.225				1.735**		
		(0.457)				(0.814)		
ΔCoalrev			0.671				-0.425	
			(0.550)				(0.736)	
ΔMinrev				-0.087				1.303**
				(0.372)				(0.587)
lgdp_percap05	-0.108***	-0.147***	-0.151***	-0.136***	-0.036*	-0.038***	-0.040***	-0.032***
	(0.033)	(0.038)	(0.036)	(0.032)	(0.019)	(0.014)	(0.013)	(0.012)
lpop_05	0.035	0.029	0.035	0.028	0.015	0.015	-0.041	0.178
	(0.022)	(0.024)	(0.024)	(0.024)	(0.191)	(0.232)	(0.203)	(0.177)
Earthquake	-0.039***	-0.040***	-0.037***	-0.040***	-0.100***	-0.032	-0.121***	-0.083**
	(0.014)	(0.013)	(0.013)	(0.013)	(0.037)	(0.067)	(0.039)	(0.040)
DURBAN	0.065	0.061	0.073	0.056	0.051**	0.039	0.030	0.060***
	(0.042)	(0.043)	(0.045)	(0.043)	(0.022)	(0.027)	(0.023)	(0.022)
DJAVA	0.107**	0.066	0.063	0.059	0.091**	0.036	0.048	0.074*
	(0.053)	(0.048)	(0.047)	(0.048)	(0.044)	(0.052)	(0.046)	(0.043)
Δlabforce	-0.012	-0.029	0.039	-0.033	0.133**	-0.040	0.048	-0.012
	(0.190)	(0.198)	(0.192)	(0.210)	(0.062)	(0.056)	(0.048)	(0.046)
dist_to_prov	0.012	0.010	0.012	0.011	0.012	0.025	0.008	0.028
	(0.023)	(0.021)	(0.023)	(0.022)	(0.022)	(0.032)	(0.023)	(0.027)
dist_to_jakarta	0.006*	0.006**	0.006**	0.006**	0.005*	0.001	0.006*	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
landlocked	-0.079	-0.065	-0.079	-0.061	-0.073	-0.019	-0.040	-0.071
	(0.060)	(0.062)	(0.064)	(0.060)	(0.064)	(0.080)	(0.064)	(0.066)
Constant	0.281	0.529	0.452	0.503	0.019	0.057	0.444	-0.101
	(0.306)	(0.342)	(0.332)	(0.342)	(0.329)	(0.406)	(0.310)	(0.313)
First stage, F stat					16.26	24.60	20.08	14.07
Hansen, P-value					0.349	0.387	0.577	0.262
Endog test, P-val					0.227	0.012	0.102	0.073
Observations	390	390	390	390	390	390	390	390
R-squared	0.182	0.100	0.103	0.098	0.122	-0.091	0.087	-0.003

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In column (7) of Table 4.5, for example, I find a standard deviation increase in a change in share of coal revenues in government budget is associated with a 1.4 (=0.046*(-0.324) = 0.014) percentage point drop in educational attainment. The magnitude of the effect is smaller for other resource dependence measures broader than coal, which may suggest that it is coal dependence in particular that is most strong negatively associated with high school completion, just as it is not positively associated with growth in per capita income. Taken together, these findings suggest that a higher dependence on resource extraction may have benefitted growth in per capita income within Indonesia in recent years, but has had no beneficial effect in reducing poverty, and may even have lowered high school completion.

Results regarding life expectancy are less consistent than those for poverty, but again with some evidence of a negative effect. In particular, while the point estimates of all four relevant resource dependence measures are negative, only one, mining dependence in GRDP (without instruments), is close to being significant, at the 10% level, as shown in column (9). For example, a standard deviation increase in a change in mining's share reduces life expectancy by (0.141*(-0.019) = 0.0019) 0.19 percent. I thus find weak evidence of a curse effect of resource dependence on life expectancy.

4.4.2 Results 2: The Effect of Resource Dependence on Development Indicators with Selective Spatial Lags

I turn next to the effects of resource dependence on development indicators when district spatial effects are taken into account. Initially I will consider only the spatial effects of neighbour resource dependence. The spatial lag measure is calculated based on the weighted average of district *i*'s neighbouring districts with regard to their resource dependence. The exact neighbour definition itself will depend on the spatial weight assumptions used.

In Table 4.6, I first present estimation results of local and neighbour resource dependence on growth in GRDP per capita based on first difference OLS (Panel A) and IV-GMM (Panel B). Three spatial definitions are used side by side as a robustness check, and these definitions slightly affect the number of observations. For instance, when eligible neighbours are defined as those districts whose centroids lie within 200 km of the centroid of the home district, this allows island districts not sharing physical borders with neighbouring districts to be included in the regressions. It is interesting to observe that, at least for the OLS estimates, regardless of the spatial definition used, the estimated effect of home district resource dependence on income is generally similar whether neighbour effects are included or not.

Table 4.4. Effects of resource dependence on development indicators, OLS Results

Dep Var:	**ΔPoverty Rate**				**ΔEducational Attainment**				**ΔLife Expectancy (log)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	miningrev	mindep	oilgasrev	coalrev	miningrev	mindep	oilgasrev	coalrev	miningrev
ΔMindep	0.046				-0.044*				-0.020			
	(0.035)				(0.026)				(0.012)			
ΔOilgasrev		-0.127				-0.067*				-0.055***		
		(0.085)				(0.035)				(0.014)		
ΔCoalrev			0.054				-0.050				0.143***	
			(0.111)				(0.052)				(0.030)	
ΔMinrev				-0.137*				-0.084**				-0.024
				(0.074)				(0.035)				(0.018)
Baseline	-0.062***	-0.059***	-0.061***	-0.062***	-0.391***	-0.397***	-0.386***	-0.394***	-0.442***	-0.455***	-0.435***	-0.441***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.050)	(0.051)	(0.051)	(0.050)	(0.035)	(0.035)	(0.035)	(0.036)
lpop_05	0.060***	0.057***	0.059***	0.058***	-0.004	-0.004	-0.004	-0.004	0.006**	0.006**	0.007***	0.005**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Earthquake	-0.004	-0.003	-0.003	-0.004	0.001	0.001	0.000	0.000	-0.004**	-0.003**	-0.003*	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
DURBAN	0.006	0.005	0.006	0.002	0.087***	0.089***	0.086***	0.087***	0.019***	0.019***	0.021***	0.019***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)	(0.015)	(0.015)	(0.015)	(0.004)	(0.004)	(0.004)	(0.004)
DJAVA	-0.012	-0.007	-0.014*	-0.008	-0.035***	-0.028***	-0.033***	-0.028***	0.031***	0.036***	0.035***	0.034***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)	(0.004)
Δlabforce	0.013	0.013	0.019	-0.001	0.005	-0.002	0.003	-0.008	-0.047***	-0.048***	-0.032*	-0.050***
	(0.033)	(0.031)	(0.028)	(0.035)	(0.030)	(0.031)	(0.031)	(0.031)	(0.016)	(0.016)	(0.016)	(0.016)
dist_to_prov	0.004	0.002	0.003	0.002	-0.008**	-0.008**	-0.008**	-0.009**	-0.001	-0.001	-0.000	-0.001
	(0.005)	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
dist_to_jakarta	-0.001**	-0.001*	-0.001**	-0.001*	0.002***	0.002***	0.002**	0.002***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
landlocked	-0.018**	-0.017**	-0.018*	-0.015**	-0.006	-0.007	-0.006	-0.005	0.003	0.002	-0.000	0.003
	(0.008)	(0.008)	(0.010)	(0.007)	(0.014)	(0.014)	(0.014)	(0.014)	(0.007)	(0.006)	(0.006)	(0.007)
Constant	-0.564***	-0.545***	-0.559***	-0.547***	0.234***	0.225***	0.238***	0.239***	1.818***	1.866***	1.761***	1.813***
	(0.069)	(0.069)	(0.068)	(0.068)	(0.074)	(0.074)	(0.076)	(0.074)	(0.155)	(0.156)	(0.155)	(0.158)
Observations	390	390	390	390	390	390	390	390	390	390	390	390
R-squared	0.328	0.343	0.322	0.344	0.303	0.302	0.298	0.305	0.513	0.521	0.529	0.511

Note : *Baseline* controls the initial level of poverty rate and life expectancy in 2005, and educational attainment in 2007 depending upon which dependent variable is used. Columns (1) to (4) and (9) to (12) use change between 2006 and 2015. Columns (5) to (8) use change for the period 2007-2015. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.5. Effects of resource dependence on development indicators, IV-GMM Results

Dep Var:	**ΔPoverty Rate**				**ΔEducational Attainment**				**ΔLife Expectancy (log)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	minrev
ΔMindep	-0.041				-0.202**				-0.019			
	(0.039)				(0.081)				(0.023)			
ΔOilgasrev		-0.023				-0.126				-0.016		
		(0.039)				(0.077)				(0.025)		
ΔCoalrev			-0.060				-0.324*				-0.131	
			(0.068)				(0.187)				(0.146)	
ΔMinrev				-0.044				-0.186**				-0.029
				(0.046)				(0.075)				(0.024)
Earthquake	-0.003	-0.003	-0.004*	-0.003	0.001	0.001	-0.001	0.001	-0.004**	-0.004**	-0.004***	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Δlabforce	-0.001	-0.004	0.010	-0.002	0.014	-0.003	-0.011	-0.018	-0.044***	-0.046***	-0.061***	-0.048***
	(0.024)	(0.027)	(0.030)	(0.023)	(0.029)	(0.031)	(0.032)	(0.032)	(0.016)	(0.016)	(0.022)	(0.016)
Baseline	-0.059***	-0.059***	-0.063***	-0.059***	-0.401***	-0.397***	-0.370***	-0.404***	-0.441***	-0.438***	-0.429***	-0.443***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.048)	(0.050)	(0.053)	(0.049)	(0.036)	(0.036)	(0.035)	(0.036)
lpop_05	0.057***	0.056***	0.060***	0.056***	-0.004	-0.003	-0.007	-0.005	0.006**	0.006**	0.004	0.006**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)
DURBAN	0.006	0.008	0.003	0.007	0.084***	0.090***	0.079***	0.087***	0.019***	0.019***	0.018***	0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.015)	(0.015)	(0.016)	(0.015)	(0.004)	(0.004)	(0.005)	(0.004)
DJAVA	-0.018**	-0.014*	-0.015**	-0.014*	-0.045***	-0.025**	-0.039***	-0.023**	0.031***	0.033***	0.030***	0.034***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.010)	(0.010)	(0.010)	(0.009)	(0.004)	(0.005)	(0.005)	(0.004)
dist_to_prov	0.003	0.003	0.003	0.002	-0.008**	-0.009**	-0.008**	-0.010***	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
dist_to_jakarta	-0.001**	-0.001**	-0.001**	-0.001**	0.002***	0.002***	0.001*	0.002***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
landlocked	-0.014**	-0.016**	-0.015*	-0.014**	-0.007	-0.006	-0.001	-0.008	0.001	0.002	0.005	0.002
	(0.007)	(0.008)	(0.008)	(0.006)	(0.014)	(0.014)	(0.015)	(0.014)	(0.007)	(0.006)	(0.008)	(0.007)
Constant	-0.532***	-0.532***	-0.561***	-0.531***	0.245***	0.213***	0.284***	0.247***	1.811***	1.799***	1.781***	1.819***
	(0.064)	(0.064)	(0.067)	(0.064)	(0.075)	(0.072)	(0.080)	(0.073)	(0.161)	(0.158)	(0.156)	(0.160)
Observations	390	390	390	390	390	390	390	390	390	390	390	390
R-squared	0.300	0.327	0.317	0.332	0.233	0.298	0.277	0.293	0.513	0.515	0.455	0.511
First-stage F-stat	14.33	19.89	29.08	12.40	14.78	12.56	10.62	11.92	22.72	9.969	9.121	11.57
Hansen P-val	0.414	0.188	0.810	0.380	0.256	0.514	-	0.294	0.438	0.695	-	0.496
Endog P-val	0.0580	0.371	0.194	0.532	0.262	0.414	0.086	0.221	0.929	0.0762	0.0156	0.775

Note : Baseline controls for poverty rate and life expectancy in 2005, and educational attainment in 2007, respectively. Columns (1) to (4) and (9) to (12) use change between 2006 and 2015. Columns (5) to (8) use change for the period 2007-2015. For ΔEducational Attainment, the instrument related with change in physical coal production is dropped. For ΔLife Expectancy (log), all instruments associated with changes in physical resource productions are removed. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1

I first check the instrument validity and endogeneity tests in Panel B to identify the most credible specifications. The instruments are the same as those used in Table 4.3, and listed in Appendix 4.2, where now twinned to include analogous neighbour measures of historical abundance and change in physical production. In each specification, my instruments are strongly correlated with the two potentially endogenous regressors in each model, home and neighbour resource dependence. The tests based on Hansen's *J* again fail to reject overidentification, with p-values all above 0.10. With my instruments have passed necessary conditions for validity for all four dependence measures across all 3 spatial definitions, endogeneity tests reject the exogeneity of resource dependence measures for columns (2), (3), (4), (6), (7), (8) and (10). I will therefore refer to OLS Panel A of Table 4.6 for columns (1), (5), (9), (11) and (12), and Panel B for the rest.

In general, results in Table 4.6 partially confirm that home district resource dependence positively affects per capita income, regardless of which spatial definition is used. However, this is now found strongly only for mining dependence in GRDP and oil/gas revenue dependence. I find even less significant association between neighbour resource dependence and home income growth. Specifically, I now find only mining dependence in GRDP of neighbour districts significantly affects real per capita income (positively), and only for two of three spatial definitions used. Home district oil and gas revenue dependence generally shows the largest effect, with point estimates ranging from 1.892 when contiguity is weighted using border length to 2.872 when spatial definition follows centroid distance. Taking the simple weighting of column (2) as an example, a one standard deviation increase in a change in the share of the oil and gas revenues (0.089) increases growth in per capita income by (2.216*0.089 =) 0.197 or almost 19.7 percent over the period 2006-2015, *ceteris paribus*. Interestingly, when neighbour resource dependence does affect home district income growth, namely for GRDP dependence under spatial definitions 1 or 3, the magnitude of neighbour district effect is greater than that of home district effect. For example, from column (1) home per capita income increases by (0.121*0.675 =) 0.081 or 8.17 percent when a change in the share of mining in real GRDP of the neighbouring area increases by one standard deviation. Whereas it only increases by (0.144*0.495) = 0.071) 7.1 percent when the home district's mining dependence increases by a standard deviation. If correct, this would imply that it is good for home district income growth to have GRDP reliant on mining, but even better if neighbouring districts are reliant on mining.

Moving to the effect of local and neighbourhood resource dependence on broader development indicators, I start with Table 4.7 (columns (1)-(12), Panel A and B) which focuses on resource effects on poverty. As before, I first focus on instrument validity and Hausman tests to identify the appropriate specifications. Happily, virtually all F tests indicate that weakness is not a problem, and Hansen's *J* statistics can not reject the null of overidentification. With necessary conditions for validity satisfied, endogeneity tests indicate that OLS specifications are adequate for all but oil and gas resource dependence under the simplest first spatial definition (column (2)), where IV-GMM is preferable.

I find as before that home district resource dependence has no significant effects on changes in poverty. For neighbour resource dependence, I also find that all revenue-based dependence measures have no effect on home district poverty. However, for two of three spatial definitions, I find that neighbouring GRDP resource dependence is associated with higher levels of poverty in the home district as shown in columns (1) and (5). In particular, in column (1), a standard deviation increase in a change in neighbour district resource share of GRDP is associated with a (0.119* 0.108) = 0.012 or 1.2 percentage point increase in the home district poverty rate. To conclude, I find little evidence that district reliance on mining (in GRDP or government budget), either with or without spatial considerations, affects home district poverty, with some exception for mining dependence in neighbouring districts.

Moving from poverty to education, Table 4.8 provides estimation results for the effects of resource dependence on the proportion of adults with high school or higher education (college or university) declared as their highest education, for OLS in Panel A and IV-GMM in Panel B. Again I first check whether my instruments pass validity tests and whether resource dependence measures are endogenous. I find that the instruments used pass relevance F tests, despite some mild evidence of weakness in column (9), and satisfy necessary conditions for exclusion restrictions. With these instruments, I find that in specifications presented by columns (2), (6) and (9), the p-values are lower than 0.100, indicating rejections of the null that specified endogenous regressor are exogenous. In addition, exogeneity of home or neighbour resource dependence is also almost rejected in columns (1) and (8). I therefore emphasize upper panel OLS estimates for models (3), (4), (5), (7), (10), (11) and (12), and lower panel IV-GMM results for models (1), (2), (6), (8) and (9).

Turning to the results, I again find with RD spatial effects added that education completion is negatively affected by three of four home resource dependence measures for all three spatial definitions between the two periods. The exception is coal revenue dependence by district governments.

Taking column (2) results under IV-GMM as an example, a one standard deviation increase in a change in home oil and gas revenues as a share of district government budget reduces the rate of high school completion by (0.087*(-0.305) =) -0.026 or 2.6 percentage points, holding all else constant. The magnitude of the point estimate falls slightly when neighbour construction is based on spatial definition 2 (share of contiguous border). Interestingly, while the impact of home district resource dependence on achievement rates is generally found to be negative, the impact of neigbour resource dependence is generally found not to be significant. Exceptions are a positive effect of oil and gas budget dependence for two of three spatial definitions (columns (2) and (6)), or mining revenue dependence more generally for spatial definition 2 in column (8). In column (2), for example, the effect of a standard deviation increase in a change in the share of oil and gas revenue dependence in neighbouring districts on the change in the share of adults with at least a high school education in the home district is a (0.087*0.270 = 0.023) 2.3 percentage point increase.

To conclude, using the appropriate OLS or IV-GMM specification, when I add spatial effects of resource dependence I still find negative effects of home district resource dependence on home district education achievement, whereas only the effects of neighbour oil and gas revenue dependence have a positive and significant effect on home education attainment.

Table 4.6. Effects on ΔGRDP Per Capita, OLS and IV-GMM, With Spatial Lag of Resource Dependence, All Spatial Definitions

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: OLS												
ΔMindep	0.495**				0.471**				0.542**			
	(0.231)				(0.226)				(0.248)			
ΔOilgasrev		0.105				0.050				0.699		
		(0.809)				(0.785)				(0.581)		
ΔCoalrev			0.096				0.103				0.277	
			(0.931)				(1.164)				(1.074)	
ΔMinrev				-0.040				-0.042				0.514
				(0.561)				(0.596)				(0.462)
ΔMindep_neighb	0.675**				0.668**				0.952*			
	(0.287)				(0.277)				(0.488)			
ΔOilgasrev_neighb		-0.504				-0.439				-1.607*		
		(0.784)				(0.692)				(0.880)		
ΔCoalrev_neighb			0.860				0.745				0.603	
			(1.198)				(1.369)				(1.407)	
ΔMinrev_neighb				-0.133				-0.144				-1.280
				(0.544)				(0.554)				(0.808)
Control Variabels	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.210	0.094	0.097	0.089	0.217	0.096	0.098	0.091	0.207	0.118	0.096	0.107
Panel B: IV-GMM												
ΔMindep	0.966**				1.181**				1.132**			
	(0.453)				(0.530)				(0.483)			
ΔOilgasrev		2.216*				1.892*				2.872**		
		(1.274)				(1.148)				(1.402)		
ΔCoalrev			-0.843				-1.251				-0.879	
			(1.239)				(1.716)				(1.531)	
ΔMinrev				1.944*				1.595				1.942*
				(0.994)				(0.970)				(1.111)

Table 4.6. Continued

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔMindep_neighb	0.411				0.185				-0.064			
	(0.321)				(0.340)				(0.625)			
ΔOilgasrev_neighb		-0.904				-0.569				-2.434		
		(1.167)				(1.021)				(1.717)		
ΔCoalrev_neighb			0.407				0.779				0.459	
			(1.222)				(1.643)				(1.797)	
ΔMinrev_neighb				-0.863				-0.596				-1.420
				(0.911)				(0.902)				(1.337)
Control Variabels	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
First-stage F stat - 1	12.21	22.51	31.35	20.43	12.84	14.97	36.50	14.72	12.89	27.17	45.05	22.22
First-stage F stat - 2	20.45	18.74	38.05	31.75	23.23	9.75	56.36	23.81	15.23	24.71	68.42	42.41
Overid, P-val	0.291	0.547	0.803	0.549	0.430	0.526	0.722	0.487	0.220	0.486	0.500	0.452
Endog P-val	0.672	0.0227	0.0491	0.0476	0.505	0.0218	0.0643	0.0976	0.737	0.0383	0.104	0.111
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.175	-0.067	0.075	-0.042	0.144	-0.053	0.072	-0.016	0.138	-0.037	0.072	0.002

Note: Spatial Definitions 1 to 3 are defined as common border (queen contiguity), length-based, and centroid distance within 200 km radius, respectively. Controls include number of earthquakes, change in district labour force, dummies for urban district and Java district, distance from each district to its provincial capital, distance of each district to Indonesia's capital, and a landlocked district dummy. Initial population and income per capita in 2005 are also controlled. First-stage F statistics (1 and 2) reports the strength of instrumental variables on each endogenous variable. The null hypothesis for overidentification tests is that the instruments are uncorrelated with the error term (instruments are valid), while the null hypothesis for endogeneity test is that the suspected endogenous variables are exogenous. *, ** and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 4.7. Effects on ΔPoverty Rate, OLS and IV-GMM, With Spatial Lag of Resource Dependence, All Spatial Definitions

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	minrev
Panel A: OLS												
ΔMindep	0.005				-0.001				-1.186			
	(0.033)				(0.034)				(1.199)			
ΔOilgasrev		-0.117				-0.123				-3.492		
		(0.076)				(0.075)				(3.574)		
ΔCoalrev			0.009				-0.029				-23.687	
			(0.255)				(0.335)				(21.144)	
ΔMinrev				-0.088				-0.097				-7.170
				(0.060)				(0.066)				(6.895)
ΔMindep_neighb	0.108*				0.110*				5.874			
	(0.059)				(0.063)				(5.586)			
ΔOilgasrev_neighb		0.005				0.014				-3.135		
		(0.077)				(0.068)				(3.489)		
ΔCoalrev_neighb			0.145				0.177				39.046	
			(0.299)				(0.363)				(34.674)	
ΔMinrev_neighb				0.003				0.017				5.475
				(0.063)				(0.068)				(5.612)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.328	0.317	0.308	0.310	0.332	0.317	0.309	0.310	0.065	0.077	0.143	0.077
Panel B: IV-GMM												
ΔMindep	-0.050				-0.025				-0.145			
	(0.040)				(0.038)				(1.075)			
ΔOilgasrev		-0.092				-0.086				-0.386		
		(0.070)				(0.069)				(2.357)		
ΔCoalrev			-0.036				-0.065				-9.499	
			(0.190)				(0.345)				(16.012)	
ΔMinrev				-0.083				-0.081				-0.011
				(0.064)				(0.060)				(2.163)

Table 4.7. Continued

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
VARIABLES	(1) mindep	(2) oilgasrev	(3) coalrev	(4) minrev	(5) mindep	(6) oilgasrev	(7) coalrev	(8) minrev	(9) mindep	(10) oilgasrev	(11) coalrev	(12) minrev
ΔMindep_neighb	0.057				0.003				0.392			
	(0.042)				(0.043)				(3.016)			
ΔOilgasrev_neighb		0.100*				0.074				0.559		
		(0.059)				(0.053)				(3.434)		
ΔCoalrev_neighb			-0.020				-0.001				14.234	
			(0.193)				(0.337)				(22.619)	
ΔMinrev_neighb				0.081				0.050				0.019
				(0.052)				(0.047)				(3.394)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.297	0.294	0.291	0.292	0.282	0.298	0.284	0.295	0.005	0.004	0.087	0.001
First stage, F stat - 1	9.69	16.69	22.89	11.93	12.24	15.22	26.29	9.43	11.22	25.72	36.64	12.42
First stage, F stat - 2	24.68	46.14	42.35	35.42	19.05	53.00	62.39	32.87	18.27	71.02	66.60	50.12
Overid P-val	0.348	0.113	0.250	0.416	0.288	0.125	0.151	0.337	0.997	0.902	0.671	0.997
Endog P-val	0.186	0.054	0.189	0.551	0.235	0.148	0.428	0.677	0.975	0.907	0.899	0.974

Note: Spatial Definitions 1 to 3 are defined as common border (queen contiguity), length-based, and centroid distance within 200 km radius, respectively. Controls include number of earthquakes, change in district labour force, dummies for urban district and Java district, distance between each district to its provincial capital, distance of each district to Indonesia's capital, and a landlocked district dummy. Initial population and income per capita in 2005 are also controlled. First-stage F statistics (1 and 2) reports the strength of instrumental variables of each endogenous variable. The null hypothesis for overidentification tests is that the instruments are uncorrelated with the error term (instruments are valid), while the null hypothesis for the endogeneity test is that the suspected endogenous variable is exogenous. *, ** and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 4.8. Effects on ΔEducational Attainment, OLS and IV-GMM, With Spatial Lag of Resource Dependence, All Spatial Definitions

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	miningrev	mindep	oilgasrev	coalrev	miningrev	Mindep	oilgasrev	coalrev	miningrev
Panel A: OLS												
ΔMindep	-0.060*				-0.058*				-0.062**			
	(0.031)				(0.031)				(0.031)			
ΔOilgasrev		-0.094*				-0.093*				-0.093*		
		(0.053)				(0.050)				(0.048)		
ΔCoalrev			-0.049				-0.050				-0.014	
			(0.081)				(0.093)				(0.102)	
ΔMinrev				-0.086*				-0.085**				-0.075*
				(0.045)				(0.043)				(0.043)
ΔMindep_neighb	0.043				0.033				0.076			
	(0.030)				(0.029)				(0.051)			
ΔOilgasrev_neighb		0.038				0.035				0.052		
		(0.060)				(0.054)				(0.067)		
ΔCoalrev_neighb			-0.006				-0.004				-0.050	
			(0.109)				(0.118)				(0.152)	
ΔMinrev_neighb				0.005				0.002				-0.017
				(0.060)				(0.055)				(0.074)
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.285	0.281	0.277	0.283	0.284	0.281	0.277	0.283	0.303	0.300	0.295	0.301
Panel B: IV-GMM												
ΔMindep	-0.265***				-0.261***				-0.193**			
	(0.085)				(0.091)				(0.092)			
ΔOilgasrev		-0.305**				-0.262**				-0.300*		
		(0.138)				(0.117)				(0.166)		
ΔCoalrev			0.453				0.618				0.608	
			(0.392)				(0.679)				(0.538)	
ΔMinrev				-0.381***				-0.327***				-0.336**
				(0.119)				(0.100)				(0.141)

Table 4.8. Continued

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	miningrev	mindep	oilgasrev	coalrev	miningrev	Mindep	oilgasrev	coalrev	miningrev
ΔMindep_neighb	0.067				0.064				-0.084			
	(0.093)				(0.080)				(0.170)			
ΔOilgasrev_neighb		0.270***				0.212***				0.352*		
		(0.103)				(0.079)				(0.190)		
ΔCoalrev_neighb			-0.587				-0.705				-0.820	
			(0.362)				(0.606)				(0.611)	
ΔMinrev_neighb				0.278***				0.203**				0.306*
				(0.101)				(0.081)				(0.177)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.170	0.261	0.242	0.237	0.176	0.267	0.234	0.252	0.210	0.277	0.255	0.260
First stage, F stat - 1	10.22	16.33	22.07	14.76	11.18	14.99	26.00	11.36	9.83	24.94	33.12	17.41
First stage, F stat - 2	18.01	46.72	44.36	41.23	24.77	52.36	64.30	40.95	11.04	68.31	63.65	35.56
Overid P-val	0.231	0.678	0.205	0.246	0.208	0.608	0.245	0.510	0.104	0.364	0.170	0.143
Endog P-val	0.126	0.038	0.246	0.191	0.213	0.080	0.600	0.118	0.075	0.149	0.708	0.187

Note: Spatial Definitions 1 to 3 are defined as common border (queen contiguity), length-based, and centroid distance within 200 km radius, respectively. Controls include number of earthquakes, change in district labour force, dummies for urban district and Java district, distance between each district to its provincial capital, distance of each district to Indonesia's capital, and a landlocked district dummy. Initial population and income per capita in 2005 are also controlled. First-stage F statistics (1 and 2) reports the strength of instrumental variables of each endogenous variable. The null hypothesis for overidentification tests is that the instruments are uncorrelated with the error term (instruments are valid), while the null hypothesis for the endogeneity test is that the suspected endogenous variable is exogenous. *, ** and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Finally, Table 4.9 reports the estimated effects of resource dependence and its spatial lag on life expectancy. Since instruments perform strongly for relevance and for overidentification, and the null hypothesis of resource dependence being exogenous is rejected in columns (2)-(3), (6)-(7) and (10)-(11), I will emphasize IV-GMM results for these specifications, and OLS for the remaining cases.

With spatial effects, I again find that the home district of neighbourhood oil and gas budget dependence has no significant effect on life expectancy regardless of the spatial definition used. I find similar results for mining revenue dependence more generally. As without spatial effects, I again find that home district coal revenue dependence has a positive and significant effect on life expectancy, but now also that neighbour district coal dependence has a significantly *negative* effect on life expectancy. This result persists for all three spatial measures. Taking column (3) under IV-GMM, for example, a standard deviation increase in the change in neighbour coal revenue dependence is associated with a (0.043*(-0.698) = -0.030) 3.0 percent decrease in life expectancy. To put this in context, the reported average life expectancy in Indonesia in 2015 stood at 61.7 years, so a 3.0 percent decrease is equivalent to 1.9 years, lowering average longevity to 59.8 years. Similar to oil and gas revenue dependence, I find little evidence that home or neighbouring GRDP dependence affects home district life expectancy, with the exception of a negative home dependence effect under the third spatial definition.

Table 4.9. ΔLife exp (log), OLS and IV-GMM, with spatial lag of RD, All Spatial Definitions

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	miningrev
Panel A: OLS												
ΔMindep	-0.021				-0.018				-0.034**			
	(0.015)				(0.015)				(0.014)			
ΔOilgasrev		-0.006				-0.009				-0.019		
		(0.025)				(0.025)				(0.022)		
ΔCoalrev			0.107*				0.110*				0.069	
			(0.059)				(0.064)				(0.056)	
ΔMinrev				0.021				0.018				-0.010
				(0.034)				(0.035)				(0.031)
ΔMindep_neighb	-0.005				-0.014				0.043			
	(0.018)				(0.017)				(0.028)			
ΔOilgasrev_neighb		-0.068***				-0.062**				-0.073**		
		(0.025)				(0.024)				(0.036)		
ΔCoalrev_neighb			0.073				0.061				0.131*	
			(0.069)				(0.070)				(0.069)	
ΔMinrev_neighb				-0.053				-0.047				-0.012
				(0.033)				(0.033)				(0.046)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.518	0.529	0.539	0.517	0.519	0.529	0.539	0.516	0.517	0.523	0.535	0.509
Panel B: IV-GMM												
ΔMindep	-0.032				-0.027				-0.031			
	(0.032)				(0.031)				(0.031)			
ΔOilgasrev		-0.049				-0.042				-0.060		
		(0.038)				(0.032)				(0.043)		
ΔCoalrev			0.669***				0.916**				0.933***	
			(0.194)				(0.421)				(0.314)	
ΔMinrev				-0.023				-0.031				-0.030
				(0.050)				(0.049)				(0.044)

Table 4.9. Continued

	Spatial Definition 1				Spatial Definition 2				Spatial Definition 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	minrev	mindep	oilgasrev	coalrev	miningrev
ΔMindep_neighb	-0.043				-0.033				-0.100			
	(0.040)				(0.040)				(0.090)			
ΔOilgasrev_neighb		0.033				0.019				0.069		
		(0.054)				(0.044)				(0.081)		
ΔCoalrev_neighb			-0.698***				-0.876**				-1.109***	
			(0.236)				(0.425)				(0.410)	
ΔMinrev_neighb				-0.022				-0.007				-0.025
				(0.053)				(0.052)				(0.070)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	374	374	374	374	385	385	385	385
R-squared	0.506	0.514	0.362	0.513	0.514	0.517	0.310	0.512	0.473	0.505	0.224	0.506
First stage, F stat - 1	15.63	21.70	15.74	17.87	16.03	14.73	14.22	16.70	15.39	19.86	19.26	14.31
First stage, F stat - 2	12.64	12.59	14.24	28.12	16.68	10.47	15.40	25.95	9.20	24.40	17.82	61.90
Overid P-val	0.665	0.905	0.293	0.346	0.824	0.807	0.289	0.624	0.736	0.997	0.306	0.332
Endog P-val	0.422	0.007	0.000	0.507	0.695	0.0101	0.00343	0.446	0.189	0.000	0.000	0.337

Note: Spatial Definitions 1 to 3 are defined as common border (queen contiguity), length-based, and centroid distance within 200 km radius, respectively. Controls include number of earthquakes, change in district labour force, dummies for urban district and Java district, distance between each district to its provincial capital, distance of each district to Indonesia's capital, and a landlocked district dummy. Initial population and income per capita in 2005 are also controlled. First-stage F statistics (1 and 2) reports the strength of instrumental variables of each endogenous variable. The null hypothesis for overidentification tests is that the instruments are uncorrelated with the error term (instruments are valid), while the null hypothesis for the endogeneity test is that the suspected endogenous variable is exogenous. *, ** and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

4.4.3 Results 3: The Effects of Resource Dependence on Development Indicators with Full Spatial Lags

This final section highlights results when all explanatory regressors are spatially lagged, rather than just resource dependence. This is to serve as a robustness check regarding the effects of resource dependence on key development indicators in Indonesia. To conserve space, I report results only for oil and gas budget dependence and GRDP mining dependence. Full results for the remaining measures are reported in Appendix 4.4 Tables A4 and A5.

Table 4.10 reports direct effects of the oil and gas dependence measure, again comparing OLS (Panel A) and IV-GMM estimates (Panel B). The first three columns show the effect of oil and gas budget dependence on growth in GRDP using the three contiguity definitions, and so similarly for other development indicators in subsequent columns. The first-stage *F* statistics show promising values and the exclusion restriction is always satisfied. As shown, tests of endogeneity show rejections of the null in columns (1)-(4), (7), and (10)-(12), indicating that these oil dependence measures should not be treated as exogenous. For per capita income, even after controlling for spatial lags of all independent variables, the effect of home district oil and gas dependence is positive for all spatial definitions, with no evidence that neighbour budget dependence has an effect. For poverty, as before there is no significant evidence that it is affected by oil and gas budget dependence in home or neighbour districts. Similarly, budget dependence remains negative for high school or higher education completion under two of three specifications, though it is possible that such dependence in neighbouring districts is beneficial for home district education completion. In particular, neighbour oil and gas revenue dependence positively affects home district education achievement for two of three spatial definitions.

Regarding the alternative resource dependence measure based on mining's share in GRDP, results with full spatial lags are reported in Table 4.11. Once again, the instruments used seem to be valid, with first-stage regressions in all specifications having *F*-statistic values generally close to or above 10. Unlike for oil and gas revenue dependence, I do not find strong evidence that the suspected measure is endogenous since p-values are generally higher than 0.10 across all columns, except for columns (7), (9) and (12). Taking columns (1) to (3), for example, growth in GRDP dependence or mining is again positive for growth if it occurs in the home district, but unlike for oil and gas revenue dependence, also if it occurs in neighbouring districts. In fact, the size of the neighbour effects are greater than those of the home district effects. Using the length-based border definition (SD2, column (2)), the spatial spillover effect is almost twice the size. These results are consistent with the specifications when only spatial effects of resource dependence are considered.

Regarding the other development outcomes, I again find similar results as when spatial effects were only added for resource dependence as in Tables 4.7, 4.8 and 4.9, where poverty is unaffected, education attainment is negatively affected, and life expectancy is negatively affected by oil and gas revenue dependence, but not GRDP dependence.

Table 4.10. Effect of the share of oil and gas revenues in local government budget on economic and development indicators, all spatial lags of explanatory variables included.

Dep. Variable:	ΔGRDP per capita			ΔPoverty Rate			ΔEducational Attainment			ΔLife Expectancy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
Panel A: OLS												
(1) ΔOilgasrev	0.078	0.044	0.628	-0.115	-0.117	-3.804	-0.074	-0.098**	-0.091**	-0.009	-0.015	-0.019
	(0.796)	(0.747)	(0.585)	(0.079)	(0.077)	(3.792)	(0.050)	(0.040)	(0.045)	(0.025)	(0.026)	(0.022)
(2) ΔOilgasrev_neighb	-0.521	-0.455	-1.537	0.007	0.019	-1.695	0.069	0.042	0.104	-0.063**	-0.055**	-0.076**
	(0.812)	(0.714)	(0.963)	(0.073)	(0.066)	(2.767)	(0.055)	(0.046)	(0.073)	(0.025)	(0.024)	(0.035)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	385	374	374	385	374	374	385	374	374	385
R-squared	0.115	0.120	0.143	0.331	0.342	0.110	0.321	0.372	0.344	0.542	0.546	0.576
Panel B: IV-GMM												
(1) ΔOilgasrev	2.396**	2.239**	2.228*	-0.100	-0.092	-0.791	-0.303**	-0.265**	-0.213	-0.065	-0.067**	-0.078*
	(1.215)	(1.126)	(1.243)	(0.078)	(0.077)	(2.968)	(0.134)	(0.121)	(0.147)	(0.041)	(0.034)	(0.043)
(2) ΔOilgasrev_neighb	-0.606	-0.320	-0.841	0.099	0.076	1.068	0.301***	0.244***	0.177	0.058	0.048	0.084
	(1.044)	(0.942)	(1.576)	(0.063)	(0.056)	(4.101)	(0.100)	(0.081)	(0.192)	(0.059)	(0.048)	(0.083)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	385	374	374	385	374	374	385	374	374	385
R-squared	-0.092	-0.094	-0.018	0.308	0.322	0.015	0.299	0.302	0.336	0.522	0.529	0.558
First-stage F stat - 1	21.28	14.70	30.38	17.28	15.59	25.04	16.77	14.90	22.63	21.82	15.38	20.19
First-stage F stat - 2	14.70	27.08	19.75	48.07	52.23	76.38	46.71	49.95	28.80	12.13	10.26	21.93
Hansen P-val	0.507	0.530	0.373	0.208	0.238	0.894	0.517	0.455	0.362	0.974	0.883	0.685
Endog P-val	0.013	0.007	0.005	0.057	0.153	0.917	0.075	0.116	0.221	0.004	0.005	0.002

***Note*:**SD is spatial definition used respectively through all specifications. Spatial controls indicate that all spatial lags of "X" variables are included.

Table 4.11. Effect of mining dependence on economic and development indicators, all spatial lags of explanatory variables included.

Dep. Variable:	ΔGRDP Per capita			ΔPoverty Rate			ΔEducational Attainment			ΔLife Expectancy (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
Panel A: OLS												
(1) ΔMindep	0.474**	0.430*	0.549**	0.001	-0.006	-1.373	-0.061**	-0.050**	-0.072**	-0.022	-0.019	-0.032**
	(0.237)	(0.236)	(0.250)	(0.035)	(0.035)	(1.341)	(0.029)	(0.023)	(0.028)	(0.015)	(0.015)	(0.014)
(2) ΔMindep_neighb	0.735**	0.730***	0.883*	0.113*	0.116*	5.408	0.045	0.025	0.102**	-0.005	-0.013	0.025
	(0.291)	(0.273)	(0.471)	(0.061)	(0.062)	(5.018)	(0.032)	(0.025)	(0.052)	(0.017)	(0.016)	(0.028)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	385	374	374	385	374	374	385	374	374	385
R-squared	0.236	0.243	0.229	0.345	0.361	0.103	0.328	0.373	0.353	0.533	0.537	0.570
Panel B: IV-GMM												
(1) ΔMindep	1.074**	1.252**	1.067**	-0.063	-0.047	-0.122	-0.169*	-0.179*	-0.186**	-0.041	-0.043	-0.044
	(0.482)	(0.554)	(0.542)	(0.053)	(0.057)	(0.966)	(0.088)	(0.099)	(0.081)	(0.036)	(0.033)	(0.031)
(2) ΔMindep_neighb	0.202	-0.008	0.000	0.042	0.002	10.871	-0.072	-0.040	-0.012	-0.049	-0.030	-0.127
	(0.431)	(0.456)	(0.834)	(0.043)	(0.043)	(9.953)	(0.117)	(0.101)	(0.166)	(0.044)	(0.043)	(0.095)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
First-stage F stat - 1	13.89	14.76	16.74	9.75	12.42	12.81	15.70	16.71	16.96	14.47	14.36	13.67
First-stage F stat - 2	19.55	22.45	14.01	24.57	16.97	12.77	16.53	20.22	12.22	10.95	12.93	6.35
Observations	374	374	385	374	374	385	374	374	385	374	374	385
R-squared	0.171	0.142	0.158	0.294	0.275	0.006	0.244	0.250	0.293	0.513	0.527	0.515
Hansen P-val	0.162	0.344	0.111	0.398	0.318	0.996	0.232	0.121	0.407	0.321	0.469	0.222
Endog P-val	0.572	0.316	0.783	0.220	0.225	0.974	0.054	0.139	0.095	0.281	0.457	0.059

***Note*:**SD is spatial definition used respectively through all specifications. Spatial controls indicates all spatial lags of “X” variables are included.

4.5 Discussion

My results in this chapter provide some evidence that, with the exception of coal revenue dependence, my resource dependence measures have had a positive impact on district per capita income over the 2006 to 2015 period, regardless of whether resource dependence is measured based on the share of local GDP or the oil and gas royalty shares of government budgets. This positive effect has also persisted when the resource dependence of neighbouring districts has been controlled for, defining neighbours based on simple contiguity boundaries, share of common border, or districts whose centroids are within a maximum distance. These many results are summarised qualitatively in Table 4.12. This robust positive association seems to contrast with Carmignani's cross-country study but is consistent with some within-country studies that have focused on local income, such as Hajkowich et al. (2011), Fleming, Measham & Paredes (2015), Weinstein et al. (2018), and Hota and Behera (2019).

For spatial effects of neighbour resource dependence on home district income, I do not find strong evidence of positive or negative spillovers, which is in line with Weber (2014) who finds no spillovers caused by resource activities in neighbouring areas. When resource dependence is measured as mining's share in district GDP, however, I find evidence that neighbour dependence spillovers positively affect home per capita income. The magnitude of pro-growth effects can actually be larger from the neighbourhood's resource dependence than that of the home district. These spillovers support Weinstein et al. (2018) for the United States who find that counties that are surrounded by oil and gas dependent neighbours may have positive effects on their earnings.

Regarding resource dependence's effects on poverty, in all specifications tested, I find no significant effect, regardless of resource dependence measure or spatial neighbour definition. This finding is similar to that of some studies, such as Bhattacharya and Resosudarmo (2015) for the case of Indonesian provinces, and confirms some findings from Weber (2012) and Patridge et al. (2013) using county-level data for the United States. The one exception I find is when controlling for spatial effects, where neighbour GRDP dependence on mining is found to be *positively* associated with the poverty rate. This adverse result is consistent with findings by Patridge et al. (2013), Edwards (2016a) and Hota Berera (2019), though these studies do not include spatial variables for home area resource dependence and poverty.

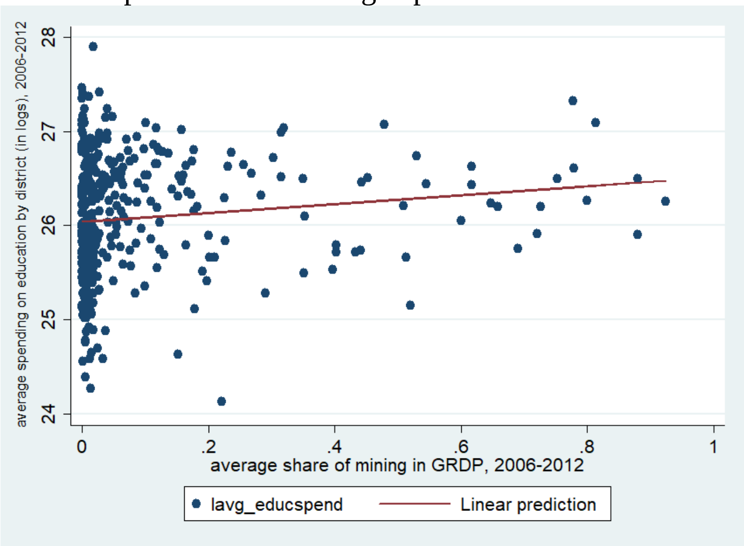
Table 4.12. Summary of results with spatial effects

Dep. Variable:	ΔGRDP			ΔPoverty Rate			ΔEducational Attainment			ΔLife Expectancy		
	SD 1	SD 2	SD 3	SD 1	SD 2	SD3	SD1	SD2	SD 3	SD1	SD2	SD3
Home effects (Spatial RD or all X Variables)												
ΔMindep	+	+	+	◦	◦	◦	-	-	-	◦	◦	-
ΔOilGasRev	+	+	+	◦	◦	◦	-	-	-	◦	◦	◦
ΔCoalRev	◦	◦	◦	◦	◦	◦	◦	◦	◦	+	+	+
ΔMinRev	+	◦	◦	◦	◦	◦	-	-	-	◦	◦	◦
Neighbouring effects (Spatial RD only)												
ΔMindep	+	+	+	+	+	◦	◦	◦	◦	◦	◦	◦
ΔOilGasRev	◦	◦	◦	◦	◦	◦	+	+	◦	◦	◦	◦
ΔCoalRev	◦	◦	◦	◦	◦	◦	◦	◦	◦	-	-	-
ΔMinRev	◦	◦	◦	◦	◦	◦	◦	+	◦	◦	◦	◦
Neighbouring effects (Spatial all X variables)												
ΔMindep	+	+	+	+	+	◦	◦	◦	◦	◦	◦	◦
ΔOilGasRev	◦	◦	◦	◦	◦	◦	+	+	◦	◦	◦	◦
ΔCoalRev	◦	◦	◦	◦	◦	◦	◦	◦	◦	-	-	-
ΔMinRev	◦	◦	◦	◦	◦	◦	◦	+	◦	-	◦	◦

Note: (+) positive effect found; (-) negative effect found; (◦) no significant effect found; SD is spatial definition

Perhaps the most robust negative effects of resource dependence are in the area of education achievement. I find that, on average, holding other factors unchanged, the share of district adults with at least a high school degree falls when there is an increase in the share of mining in local GDP, or the share of oil and gas revenues in district budgets, or the share of oil, gas and coal, leaving only the share of coal that is insignificant in any specifications used. These results for home district resource dependence persist when neighbour resource dependence measures are also controlled. My results confirm the majority of resource effects on education studies such as Edwards (2016a), Douglas and Walker (2016), and more recently by Zuo et al. (2019) and Carpenter, et al. (2019).

Figure 4.5. Scatter plot between mining dependence and education expenditure



Source: *Author's calculation*

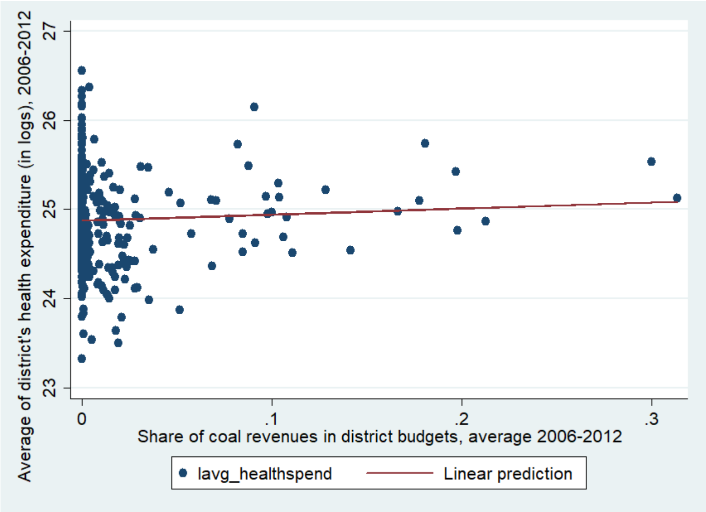
One might wonder whether lower educational attainment in more resource dependent districts is being driven by demand or supply-side effects. For example, perhaps more resource dependent district governments see higher education provision as less necessary, and so fund fewer high schools or post-secondary institutions (see e.g. Gylfason (2001), Stijns (2005), and James (2017)). Alternatively, perhaps the parents of teens or the teens themselves in more resource dependent districts opt not to go to the schools and institutes provided. I investigate this briefly using some available data associated with district per capita education expenditures during the period 2006-2012.

As presented in Figure 4.5, I find a positive correlation between resource dependence and education spending by district government, contrary to a supply side explanation. Perhaps commodity booms create an incentive for young people to delay continuing their education to a higher level, or for young adults to drop-out of college or university in favor of entering entry-level resource jobs (see Douglas and Walker, 2016). This might suggest that negative effects of resource dependence on educational achievement is working on the demand side. Note that demand-side explanations do not necessarily mean that oil, gas and coal companies alone tend to hire direct entry workers, since there may also be more demand for entry level workers from sectors that closely support resource extraction activities. For example, oil down-stream and up-stream activities have long been identified as contributing to growth in regions where resource extraction occurs, including employment demand for low skill workers as constrasted with employment demand induced by non-mining sectors (see Marchand and Weber, 2016; and Weber (2014), Zuo et al. (2019)). Some studies have also found a positive effect of mining growth on non-mining sectors (Weber, 2014; Fleming et al. (2015), Weinstein, 2015). Unfortunately a detailed examination of resource sector effects on employment of school leavers is outside the scope of this chapter, owing in part to incompleteness of district level data within the time period considered.

With respect to spatial effects of resource dependence on education, I find in contrast that an increase in neighbour's share of oil and gas revenue *increases* the share of adults with at least a high school degree, in two of three spatial definitions used. These findings differ from the insignificant spatial effects found by Weber (2014) on education in the United States, though the author focused only on changes in natural gas production. As the existence of empirical studies controlling spatial spillovers of resource dependence on education for developing countries is lacking, it is hard to speculate why neighbour government dependence on oil and gas is likely to improve home district high school completion rates of adult residents. One possibility is that an oil boom experience by neighbouring district(s) may increase demand for more highly skilled adults in upstream or downstream industries that locate in only rough proximity to oil extraction sites. Home district governments in non-resource districts may also react by spending more in education to compete with mining-based neighbouring areas to maintain their regional economy and attract non-mining based industries. This possibly would lead to a better supply of education in the home district that would promote better school completion rates for local young residents.

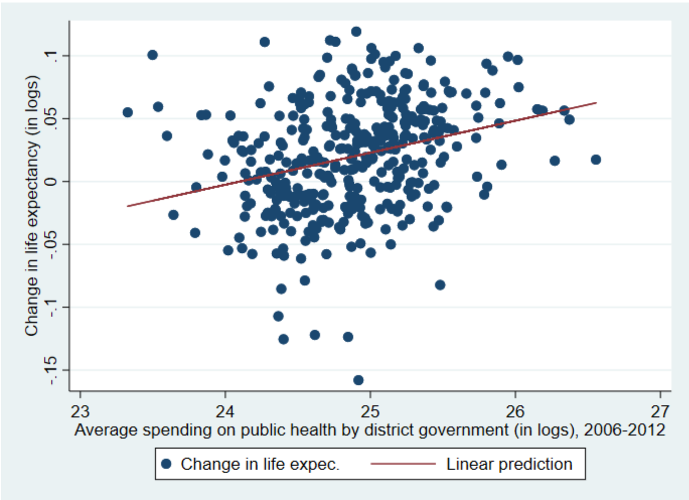
Finally with respect to resource dependence's effect on health outcomes. I find no compelling evidence that mining's share in GRDP or oil and gas revenue dependence affects average life expectancy at birth in home districts. However, I find that home district coal revenue dependence in government budgets is positively associated with life expectancy, while neighbour coal dependence is negatively associated with home district life expectancy. I will discuss each in turn. My home coal dependence results are similar to those found by Alexeev and Conrad (2011), Cotet and Tsui (2013), and El Anshasy and Katsaiti (2015), for cross-country investigation, though these studies test for the effect of hydrocarbons generally rather than coal. The positive effects found by these studies also become insignificant when resources are measured aggregately, and geographic factors are also controlled. As argued by Acemoglu et al. (2019), positive effects may result as resource wealth enables jurisdictions to allocate more spending on healthcare services. Higher public spending may also reflect better political and economic institutions, which themselves are believed to benefit development outcomes, including health outcomes (El Anshasy and Katsaiti, 2015).

Figure 4.6. Scatter plot between health spending and coal revenues, period 2006-2012



Source: *Author's calculation*

Figure 4.7. Scatter plot between life expectancy and spending on health, period 2006-2012



Source: *Author's calculation*

For Indonesia, coal mining actitivies have expanded since the 2000's due to a rapid growth in overseas demand from China, India, and some European countries. District governments dominated by coal mining operations are very likely to have received higher government budgets as a result, which under decentralisation funding schemes generate resource royalties that are partially returned to districts of origin. Such coal revenues may possibly help local governments to spend more on health infrastructure such as community health centres in sub-district areas and villages, as well as hospitals in targetted areas. More money for health expenditures may also come in the form of Corporate Social Responsibility (CSR) programmes of coal companies, whereby they fund local communities to raise public awareness regarding the benefits of child immunisation and breasfeeding. To test this conjecture, I again use health expenditure data of district governments and link it to the average share of coal revenues in 390 districts over 2006-2012. As shown in Figure 4.6, I find a slight positive correlation between coal budget dependence and district budget spending on public health. Subsequently, I also plot the correlation between public health spending and change in life expectancy in Figure 4.7. Not surprisingly, this shows a strong positive correlation, implying that spending on health increases life expectancy at district level.

It might initially seem odd that neighbour district coal revenue dependence lowers home district life expectancy, when home district dependence raises it. A negative impact of coal on health outcomes appears in many empirical studies that link it with, for example, worsened spending on human capital investments due to poor institutional development in resource-abundant countries (Acemoglu and Robinson, 2005, 2019), or a destructive effect of air pollution caused by the toxins and pollutants released when coal is burned. The first argument seems not strongly supported by the correlation evidence in Figure 4.7. The latter argument is also weak for Indonesia as the country does not operate many coal-fired power plants and more than 80% of coal produced is exported overseas.[103] One might argue that coal mining activities have burned land, but the deforestation associated with coal mining is greatly limited compared to that for palm oil plantations.

I argue instead that two other factors may cause neighbour district dependence on coal revenues to negatively affect home district life expectancy or health. The first regards contamination of air and water. Coal mining activities in Indonesia, particularly for small-scale companies, rely on trucks for transporting coal from the mining sites (generally in remote areas) to centralised storage locations before being loaded onto barges. Their transport often uses road facilities in adjacent districts, which pollutes the air inhaled by adjacent local residents. A prime example is contamination from coal dust particles. Similarly, significant reductions in water quality have resulted from barge transport through main rivers. Water

[103] Coal domestic consumption in Indonesia during the period this study observed was on average around 20%. Only since 2018 the Indonesian government, under the new plan strategy, announced it would build 58 greenfield coal-fired power plants by 2027, to adapt to potential growth in the population and accelerated industrialisation. (see https://www.worldcoal.com/power/22112018/coal-to-remain-king-in-indonesia-for-now/).

from rivers has been the main source for local water companies in downstream districts to supply “clean” water to local residents.[104]

A second potential reason for neighbour coal dependence to depress home district life expectancy is economically-motivated migration by healthy young people. Work-related migration is common in Indonesia and coal-boom districts may provide better work opportunities that attract young ambitious adults. People with better health may be more likely to move as they are better capable of adapting to the new area. Such out-migration from non-coal districts may reduce the number of healthier adults there, and this could possibly depress estimates of life expectancy in the home district.

4.6 Conclusions

This chapter has tested for effects of natural resource dependence on development indicators beyond income, using unique district level data in Indonesia between 2006 and 2015. As in previous chapters, I have used four major measures of resource dependence and addressed possible endogeneity of these measures using instruments based on historical abundance and change in physical production. I also especially controlled for spatial spillover effects of neighbouring districts on home district outcomes, using three common methods of identifying and weighting relevant neighbours. This work is novel, as to my knowledge no empirical resource effect studies that incorporate spatial effects have yet been conducted in developing countries.

As in previous chapters, I have found that GRDP dependence on mining or government budget dependence on oil and gas contributed significantly to raising income per capita, now also when neighbour dependence is included, using three alternative definitions of neighbour. This finding, however, does not tell us about the distribution of the additional income across households or individuals.

I address this omission by examining the effects of resource dependence on broader development indicators, beginning with poverty. In contrast to per capita income, I find that rising resource dependence failed to affect poverty rates at district level, neither lowering nor increasing the proportion of poor households. Even less happily, almost all my measures of resource dependence have a negative impact on the share of adults with at least high school

[104] See https://www.thejakartapost.com/news/2013/12/04/coal-rush-ravages-indonesian-borneo.html

education. However, there is some evidence that rising neighbour oil and gas revenue dependence, or aggregate mining revenue dependence are positively associated with home district education achievement. There is also an opposite divergence between home and neighbour resource dependence effects on life expectancy for coal revenue dependence in particular, where home dependence raises it but neighbour dependence lowers it. In some specifications I find neighbour effects seem to matter, although it is hard to generalise as it sometimes has an opposite effect of the home dependence coefficient.

To conclude, it is worth investigating the impact of resource dependence on multiple development indicators in developing countries. This is because natural resources have the potential to play a critical role in the development process. Yet as finer within-country jurisdictions are used in such studies, it becomes more necessary to control for spatial spillovers of characteristics of one area on the development of its neighbours. While including spatial effects, my study does not test potential channels through which spillovers may be occuring, such as local labour markets and migration patterns. These factors may serve as important causal mechanisms through which resource reliance in one district influences measured education completion rates in another, or life expectancy. This question of causal channels is open for subsequent investigation and worth pursuing.

4.7 Appendix:

Appendix 4.1. Table A1. Definition of Variables and Data Sources

Variable	Definition	Source
Δ Real GRDP per capita (in logs)	The natural logarithm of difference of real GRDP per capita, formulated as: ΔGRDP per capita $= ln\,(\frac{GRDP_{percapita,2015}}{GRDP_{percapita,2007}})$	INDO DAPOER World Bank (can be downloaded here: https://datacatalog.worldbank.org/dataset/indonesia-database-policy-and-economic-research) The Indonesian National Statistical Agency (BPS) (see https://www.bps.go.id/)
ΔPoverty rate	The difference in poverty rate, between 2015 and 2006	BPS, Poverty Publications
ΔLife expectancy (log)	The difference in life expectancy between 2015 and 2006	BPS, Human Development Publications
ΔEduc_attain	The difference in the share of district population that finished at least high school, between 2015 and 2007	BPS, National Survey of Labour Force (raw data), 2007 and 2015
Earthquake	The number of earthquake events at the district level	Indonesian National Board for Disaster Management (BNPB). Can be accessed online here: http://dibi.bnpb.go.id/dibi/
ΔLabour force partic.rate	The change in labour force participation rate between 2015 and 2006	INDO DAPOER World Bank, BPS
GRDP per capita, 2005 (in logs)	Natural logarithm of initial GRDP per capita in 2005	INDO DAPOER World Bank, BPS
Poverty Rate, 2005	Initial poverty rate in 2005	BPS, Poverty Publications
Life Expectancy (in logs), 2005	Natural logarithm of initial life expectancy in 2005	BPS, Human Development Publications
Educational Attainment, 2007	Share of local population that has secondary education degree or better in 2007	BPS, National Survey of Labour Force (raw data), 2007
Population, 2005 (in logs)	Natural logarithm of initial population in 2005	BPS
DURBAN	Dummy urban status (municipalities) = 1 if city status, = 0 if regency	Identity of urban district/municipality is taken from the Ministry of Home Affairs, the Republic of Indonesia
DJAVA	Dummy of Java Island = 1 if the districts are located on Java Island, = 0 otherwise	-
Distance to Provincial Capital	Calculated by measuring straight line distance (in km) between each district and its respective province within provincial boundary.	Shapefile administrative district data from Indonesia GeoSpatial Portal (Geospatial Information Board of Indonesia). Modified following 390 administrative districts in 2003.

Variable	Definition	Source
Distance to Jakarta	Calculated by measuring straight line distance (in km) between each district and Indonesia's Presidential Palace in Jakarta.	Shapefile administrative district data from Indonesia GeoSpatial Portal (Geospatial Information Board of Indonesia). Modified following 390 administrative districts in 2003.
Landlocked	Dummy status = 1 if district is landlocked, = 0 otherwise.	Shapefile data from Indonesia GeoSpatial Portal (Geospatial Information Board of Indonesia)
ΔMining Dependence (Mindep)	The difference in mining dependence between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia
ΔOilGas Revenue (Oilgasrev)	The difference in oil and gas revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
ΔCoal Revenue (Coalrev)	The difference in coal revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
ΔMining Revenue (Minrev)	The difference in mining revenue shares, between 2015 and 2006	Ministry of Finance, Republic of Indonesia; The Audit Board of the Republic of Indonesia; BPS
oilgasabundance	The number of major and minor oil and gas fields in the 1970's production period in all Islands of Indonesia. Major oil and natural gas fields are weighted by 1, and all minor fields are weighted by 0.25. So, if district A has a 10 minor oil/gas fields location, therefore: $District_A = 10 \times 0.25 = 2.5$	Ooi Jin Bee (1982)
coalabundance	The share of coal deposit areas (shown by first generation coal agreement contract introduced by Leeuwen (1994, 2017)) in the total area of the respective district.	Friederich & Leeuwen (2017)
Δoilprod	The change in oil production (in barrels) between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia
Δgasprod	The change in natural gas production (in MMBTU) between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia
Δcoalprod	The change in coal land rents and royalties between 2015 and 2006	Ministry of Energy and Mineral Resources, Republic of Indonesia

Appendix 4.2. Table A2, A3, A3.1. Instrument Summary

Dependent Variable: ΔGRDP per capita		
Resource Dependence Measure	**Instruments**	
	Resource Abundance	**Change in physical resource production**
ΔMindep	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production
ΔOilgasrev	- Oil + Natural Gas *i* Abundance 1970's	- Change in oil production - Change in gas production
ΔCoalrev	- Coal Abundance 1980's *i*	- Change in coal production
ΔMinrev	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production
ΔMindep_neighb	- Oil + Natural Gas Abundance 1970's *i *W* - Coal Abundance 1980's *I *W*	- Change in oil production* *W*
ΔOilgasrev_neighb	- Oil + Natural Gas *i* Abundance 1970's * *W*	- Change in oil production* *W*
ΔCoalrev_neighb	- Coal Abundance 1980's *I *W*	- Change in coal production * *W*
ΔMinrev_neighb	- Oil + Natural Gas Abundance 1970's *i *W* - Coal Abundance 1980's *I *W*	- Change in oil production* *W*
Dependent Variable: ΔPoverty Rate		
Resource Dependence Measure	**Instruments**	
	Resource Abundance	**Change in physical resource production**
ΔMindep	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production - Change in coal production
ΔOilgasrev	- Oil + Natural Gas *i* Abundance 1970's	- Change in oil production - Change in gas production
ΔCoalrev	- Coal Abundance 1980's *i*	Change in coal production
ΔMinrev	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production - Change in coal production
ΔMindep_neighb	- Oil + Natural Gas Abundance 1970's *i* * *W* - Coal Abundance 1980's *i* * *W*	- Change in oil production* *W* - Change in gas production* *W* - Change in coal production* *W*
ΔOilgasrev_neighb	- Oil + Natural Gas *i* Abundance 1970's * *W*	- Change in oil production* *W* - Change in gas production* *W*
ΔCoalrev_neighb	- Coal Abundance 1980's *i* * *W*	- Change in coal production * *W*
ΔMinrev_neighb	- Oil + Natural Gas Abundance 1970's *i* * *W* - Coal Abundance 1980's *i* * *W*	- Change in oil production* *W* - Change in gas production* *W* - Change in coal production* *W*

Notes: **W** indicates spatial weight matrix / spatial definition. When two specified endogenous measures are included in each model (e.g. ΔMindep and ΔMindep_neighb), all excluded instruments (including instruments designed for spatial lags of resource dependence) will be used in each measure.

Table A3. Instrument Summary (Cont'd)

Resource Dependence Measure	Instruments: Resource Abundance	Instruments: Change in physical resource production
Dependent Variable: ΔEducational Attainment		
ΔMindep	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production
ΔOilgasrev	- Oil + Natural Gas *i* Abundance 1970's	- Change in oil production - Change in gas production
ΔCoalrev	- Coal Abundance 1980's *i*	- Change in coal production
ΔMinrev	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production
ΔMindep_neighb	- Oil + Natural Gas Abundance 1970's *i* * *W* - Coal Abundance 1980's *i** *W*	- Change in oil production* *W* - Change in gas production* *W*
ΔOilgasrev_neighb	- Oil + Natural Gas *i* Abundance 1970's* *W*	- Change in oil production* *W* - Change in gas production* *W*
ΔCoalrev_neighb	- Coal Abundance 1980's *i** *W*	- Change in coal production* *W*
ΔMinrev_neighb	- Oil + Natural Gas Abundance 1970's *i** *W* - Coal Abundance 1980's *i** *W*	- Change in oil production* *W* - Change in gas production* *W*
Dependent Variable: ΔLife Expectancy (log)		
ΔMindep	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production
ΔOilgasrev	- Oil + Natural Gas *i* Abundance 1970's	- Change in oil production
ΔCoalrev	- Coal Abundance 1980's *i*	- Change in coal production
ΔMinrev	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	
ΔMindep_neighb	- Oil + Natural Gas Abundance 1970's *i* * *W* - Coal Abundance 1980's *i** *W*	- Change in oil production
ΔOilgasrev_neighb	- Oil + Natural Gas *i* Abundance 1970's* *W*	- Change in oil production
ΔCoalrev_neighb	- Coal Abundance 1980's *i** *W*	Change in coal production
ΔMinrev_neighb	- Oil + Natural Gas Abundance 1970's *i** *W* - Coal Abundance 1980's *i** *W*	

Notes: **W** indicates spatial weight matrix / spatial definition. When two specified endogenous measures are included in each model (e.g. ΔMindep and ΔMindep_neighb), all excluded instruments (including instruments designed for spatial lags of resource dependence) will be used in each measure.

Table A3.1. Instrument Summary (Cont'd) - All Spatial X Variables

Dependent Variable: ΔEducational Attainment		
Resource Dependence Measure	**Instruments**	
	Resource Abundance	**Change in physical resource production**
ΔMindep	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production
ΔOilgasrev	- Oil + Natural Gas *i* Abundance 1970's	- Change in oil production - Change in gas production
ΔCoalrev	- Coal Abundance 1980's *i*	- Change in coal production
ΔMinrev	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	- Change in oil production - Change in gas production
ΔMindep_neighb	- Oil + Natural Gas Abundance 1970's *i* * W - Coal Abundance 1980's *i** W	
ΔOilgasrev_neighb	- Oil + Natural Gas *i* Abundance 1970's* W	- Change in oil production* W - Change in gas production* W
ΔCoalrev_neighb	- Coal Abundance 1980's *i** W	- Change in coal production* W
ΔMinrev_neighb	- Oil + Natural Gas Abundance 1970's *i** W - Coal Abundance 1980's *i** W	- Change in oil production* W
Dependent Variable: ΔLife Expectancy (log)		
Resource Dependence Measure	**Instruments**	
	Resource Abundance	**Change in physical resource production**
ΔMindep	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	
ΔOilgasrev	- Oil + Natural Gas *i* Abundance 1970's	- Change in oil production
ΔCoalrev	- Coal Abundance 1980's *i*	- Change in coal production
ΔMinrev	- Oil + Natural Gas Abundance 1970's *i* - Coal Abundance 1980's *i*	
ΔMindep_neighb	- Oil + Natural Gas Abundance 1970's *i* * W - Coal Abundance 1980's *i** W	
ΔOilgasrev_neighb	- Oil + Natural Gas *i* Abundance 1970's* W	- Change in oil production* W
ΔCoalrev_neighb	- Coal Abundance 1980's *i** W	- Change in coal production * W
ΔMinrev_neighb	- Oil + Natural Gas Abundance 1970's *i** W - Coal Abundance 1980's *i** W	

Notes: **W** indicates spatial weight matrix / spatial definition. When two specified endogenous measures included in each model (e.g. ΔMindep and ΔMindep_neighb), all excluded instruments (including instruments designed for spatial lags of resource dependence) will be used in each measure.

*Appendix 4.3. Fig A1***.** *Map of five major islands of Indonesia and interactions highlighted among districts within the respective island*

Source: Indonesia GeoSpatial Board, modified for illustrative purpose by the author. Maps produced by GeoDa version 1.12 (http://geodacenter.github.io/download.html)

Appendix 4.4. Table A4-A5. Effects on GRDP and Poverty, OLS and 2SLS Results, All Spatial Lags of the Explanatory Variables Included

Dep. Var:	ΔGRDP Per Capita						ΔPoverty Rate					
	SD1	SD1	SD2	SD2	SD3	SD3	SD1	SD1	SD2	SD2	SD3	SD3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	coalrev	miningrev	coalrev	miningrev	coalrev	miningrev	coalrev	minrev	coalrev	minrev	coalrev	minrev
Panel A: OLS												
ΔCoalrev	0.096		0.102		0.388		-0.035		-0.069		-23.604	
	(0.943)		(1.119)		(1.024)		(0.265)		(0.317)		(20.701)	
ΔCoalrev_neighb	0.801		0.558		0.001		0.168		0.157		38.293	
	(1.400)		(1.467)		(1.589)		(0.326)		(0.361)		(33.452)	
ΔMinrev		-0.050		-0.041		0.501		-0.097		-0.101		-7.242
		(0.569)		(0.594)		(0.479)		(0.065)		(0.069)		(6.764)
ΔMinrev_neighb		-0.167		-0.189		-1.335		0.006		0.016		6.032
		(0.569)		(0.586)		(0.846)		(0.069)		(0.071)		(5.979)
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	385	385	374	374	374	374	385	385
R-squared	0.115	0.110	0.119	0.116	0.123	0.139	0.322	0.327	0.333	0.340	0.171	0.118
Panel B: 2SLS												
ΔCoalrev	-0.723		-0.904		-0.593		-0.182		-0.235		-27.638	
	(1.207)		(1.750)		(1.547)		(0.191)		(0.309)		(25.436)	
ΔCoalrev_neighb	-0.150		0.009		-0.983		0.139		0.196		41.553	
	(1.390)		(1.779)		(2.132)		(0.214)		(0.325)		(37.603)	
ΔMinrev		2.004**		1.684*		2.203**		-0.114*		-0.111*		-6.906
		(0.968)		(0.924)		(1.123)		(0.069)		(0.067)		(6.597)
ΔMinrev_neighb		-0.752		-0.506		-1.556		0.095*		0.063		12.545
		(0.846)		(0.857)		(1.389)		(0.055)		(0.049)		(11.709)
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	385	385	23.31	11.63	24.88	9.47	30.83	11.98
R-squared	0.088	-0.050	0.092	-0.032	0.086	0.002	42.76	35.90	69.79	32.96	69.62	55.69
First-stage F stat - 1	27.95	20.62	34.08	14.41	38.81	18.49	374	374	374	374	385	385
First-stage F stat - 2	29.22	26.84	52.04	21.12	55.67	35.81	0.296	0.294	0.285	0.290	0.169	0.100
Hansen P-val	0.737	0.260	0.694	0.202	0.367	0.156	0.291	0.532	0.112	0.402	0.706	0.996
Endog P-val	0.0470	0.149	0.0473	0.270	0.121	0.181	0.151	0.677	0.346	0.599	0.808	0.965

Table A5. *Effects on Education and Life Expectancy, OLS and 2SLS Results, All Spatial Lags of the Explanatory Variables Included*

	ΔEducational Attainment						ΔLife Expectancy (log)					
	SD1	SD1	SD2	SD2	SD3	SD3	SD1	SD1	SD2	SD2	SD3	SD3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	coalrev	minrev	coalrev	minrev	coalrev	minrev	coalrev	minrev	Coalrev	minrev	coalrev	minrev
Panel A: 2SLS												
ΔCoalrev	-0.045		-0.001		0.023		0.107*		0.112*		0.093	
	(0.081)		(0.092)		(0.100)		(0.063)		(0.066)		(0.060)	
ΔCoalrev_neighb	-0.033		-0.068		-0.032		0.060		0.038		0.064	
	(0.109)		(0.108)		(0.143)		(0.072)		(0.073)		(0.071)	
ΔMinrev		-0.081**		-0.080**		-0.072**		0.016		0.012		-0.006
		(0.034)		(0.035)		(0.036)		(0.032)		(0.034)		(0.028)
ΔMinrev_neighb		0.010		0.001		0.005		-0.058*		-0.051		-0.052
		(0.049)		(0.047)		(0.065)		(0.031)		(0.032)		(0.043)
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	374	374	374	374	385	385	374	374	374	374	385	385
R-squared	0.372	0.378	0.367	0.374	0.406	0.412	0.547	0.533	0.550	0.536	0.577	0.566
Panel B: 2SLS												
ΔCoalrev	0.408		-0.630		-0.489		0.732***		0.971**		0.937**	
	(0.369)		(0.719)		(0.537)		(0.221)		(0.440)		(0.379)	
ΔCoalrev_neighb	-0.634*		0.295		0.304		-0.848***		-0.982**		-1.250**	
	(0.338)		(0.631)		(0.580)		(0.306)		(0.452)		(0.552)	
ΔMinrev		-0.423***		-0.190**		-0.136		-0.035		-0.062		-0.037
		(0.134)		(0.088)		(0.086)		(0.032)		(0.050)		(0.033)
ΔMinrev_neighb		0.354***		0.093		0.031		-0.014		0.018		-0.049
		(0.123)		(0.077)		(0.126)		(0.044)		(0.054)		(0.061)
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
First-stage F stat - 1	8.71	14.87	8.38	11.15	7.69	14.94	12.20	16.97	12.11	16.09	12.00	12.16
First-stage F stat - 2	11.07	40.34	14.75	38.52	12.87	56.98	10.17	21.93	13.86	22.99	11.60	63.34
Observations	374	374	374	374	385	385	374	374	374	374	385	385
R-squared	0.291	0.262	0.311	0.366	0.371	0.408	0.318	0.528	0.286	0.525	0.261	0.563
Hansen P-val		0.174		0.417		0.153	0.259	0.175	0.265	0.293	0.353	0.144
Endog P-val	0.274	0.132	0.147	0.142	0.312	0.271	0.000	0.183	0.003	0.209	0.000	0.106

5 CHAPTER FIVE

5.1 Conclusions

This thesis has provided empirical findings regarding the effects of resource dependence on local development indicators in the post-decentralisation era in Indonesia. In Chapter Two, I find that most measures of resource dependence are positively associated with district per capita income in Indonesia. The one exception, coal revenue dependence sometimes has a negative effect, but in most specifications is insignificant. Positive effects are robust across different measures of resource dependence, to whether analysis is conducted using annual fixed effects or first difference estimation to control for unobserved regional differences, and to the the use or exclusion of instrumental variables. Indonesia thus joins many (but not all) other within-country studies in finding that resource dependence aids rather than hinders growth in income.

Subsequently, Chapter Three investigates some potential causes through which greater resource dependence might raise aggregate income per person at the district level. I test the causal channels of spillovers to the manufacturing sector, net enrollment rates of high school aged children (note that this measure is distinct from high school completion rates), institutional capacity within local governments, and the proportion of district government spending devoted to capital expenditures. Using a three-step estimation strategy, I find some evidence of a positive impact of resource dependence on all channels selected, with the exception of public capital spending. However, these channels do not adequately explain the causes of district growth, as can be seen from the residual unexplained effects. The causal channel I found to best bridge the relationship between resource dependence and growth in Indonesia is institutional quality. That is, districts appear to use the revenues provided from resource dependence to increase their institutional capacity, which in turn promotes growth in per capita income.

In complementary analysis, Chapter Three also tests the ‘contingent curse’ hypothesis of Mehlum, Moene & Torvik (2006). First, I test whether resource dependence aids the growth of districts that initially have good institutional quality, but harms growth for those who do not. Using an administrative capacity measure of bureaucracy as a proxy for local institutional quality for the longer period 2007-2015, I divide my 390 district sample into two equal sized groups: districts that initially have stronger institutional quality and those which have weaker. The results do not provide evidence that resource dependence weakens growth in districts that have weaker initial institutions. Instead, I find that rising resource dependence helps per capita income to grow faster in the weaker district sample. In contrast, when I do the same process using the shorter period 2010-2015 with a more comprehensive measure of institutional qualit. I find weak evidence more in line with Mehlum et al.'s hypothesis, but it is not robust.

I thus also formally test Mehlum et al.'s hypothesis by adding an interaction term between each resource dependence measure and initial level of institutional quality. Again in my most credible specification, I find the coefficient on the interaction term is negative and significant, suggesting that increased initial district institutional quality actually reduces the positive effect of resource dependence on district growth. However, when analysed using a better institutional quality measure, the coefficient on the interaction term is still negative but insignificant.

Finally, Chapter Four completes the investigation by examining the (overall) effects of resource dependence on broader development outcomes, and by focusing on the spatial effects of resource dependence in neighbouring districts on outcomes of interest in home districts. Additional controls for district absolute geographical features are also included. For robustness, I introduce three spatial definition criteria to determine neighbouring districts: simple contiguity, contiguity weighted by border length, and distance between centroids. The broader development outcomes considered, with and without spatial lags, are poverty rates, the proportion of the adult population with at least high school completion, and life expectancy.

To summarize, I find that the positive effects of resource dependence on per capita income remain persistent in some specifications, regardless of whether additional geographic factors are included or different spatial definitions used. Perhaps surprisingly, I then find no effect of resource dependence on poverty rates in any specifications. Even less optimistically, I find that home district resource dependence hinders the education attainment of adults whether with or without the inclusion of neighbour resource dependence, more in line with a curse hypothesis. There is suggestive evidence this effect may be working through education demand rather than supply. I also find that in general life expectancy is unaffected by home resource dependence, with the exception of coal revenue dependence. With regards to spatial spillover effects, I find several instances where neighbouring resource dependence also affects development outcomes in the home district, indicating the importance of including spatial controls. A prime example of this is a curse effect of neighbour coal revenue dependence on home district life expectancy when home district coal dependence is positively associated with life expectancy. Another example is a positive effect caused by an increase in neighbour oil revenue dependence on education attainment in the home district.

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